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Multi-System Optimization: Intermittent Production, Flexible Demand, Emerging Technologies

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Multi-System Optimization: Intermittent Production, Flexible Demand, Emerging Technologies

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Multi-System Optimization: Intermittent Production, Flexible Demand, Emerging Technologies

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Modern life depends on cheap and reliable energy. The energy system powers just about every other major sector including buildings, transportation, food systems, and water systems. However, the energy production and consumption processes produce large amounts of pollution and greenhouse gases, they waste most of the energy they produces, and the negative externalities cascade to other systems. Furthermore, the environmental concerns, inefficiencies, and adjacent system effects have the largest impacts on the most vulnerable — those of us who live in areas with higher air pollution, have less efficient homes and cars, and as a result spend more of their income on energy while getting less out of it. New technologies and the purposeful integration of energy with other sectors via multi-systems optimization techniques can address some of these issues.

Clean energy technologies like wind and solar can produce energy with no fuel costs and virtually zero negative environmental effects. However, these technologies are intermittent and the times they produce energy do not always align with when energy is needed. Furthermore, while the costs of these technologies are falling rapidly, they still require high up-front costs that investors and homeowners are hesitant to pay and that vulnerable

populations simply cannot afford to pay. These drawbacks can be overcome by finding ways to use clean energy when it is available and sharing the costs of the technologies among larger groups. While there is a large body of research investigating clean energy adoption and costs, there is limited work examining how to match energy demand from different systems with the intermittent sources of energy or how community investment can drive down individual cost.

The goal of this dissertation is to advance research related to multi-systems optimization by examining interdependencies between the energy sector and other systems. These interdependencies can encourage clean energy adoption by aligning the flexible loads of those systems with the intermittent supply of renewables. Furthermore, we investigate ways to minimize an individual or a community's barrier of entry into the clean energy space. The projects in this dissertation investigate novel methods for decision-making on clean energy investment and dispatch using multi-system optimization techniques and case studies informed by real-world data. The three core chapters of this dissertation begin with development of an applied energy and transportation system optimization model to assess how autonomous vehicles could decarbonize electricity and transportation and then shift to how food, energy, and water are connected and could provide mutually reinforcing benefits at the community level and in an agricultural setting.

Chapter 2 investigates the possible climate change impacts of the anticipated growth in shared autonomous vehicles (SAVs). The developed multi-system optimization model integrates the electricity and transport sectors, computes endogenous technology adoption, and distinguishes SAVs from privately owned vehicles (POVs) to explore the contributions of SAVs to climate change mitigation. Our results show that widespread SAV adoption lowers costs and emissions, and that these desirable outcomes remain true even if SAVs induce double the VMT of the POVs they replace. Furthermore, we find that SAVs dramatically accelerate the market penetration of electric vehicles, and the environmental and economic benefits of this electrification trend are larger if electric SAV charging can be optimally aligned with renewable electricity generation. We find that in the short to medium term, SAV adoption can be a more impactful lever than a carbon tax for decarbonizing vehicle travel.

The multi-system optimization model in Chapter 2 investigated how energy decisions at the urban level impacted both the power and transportation sectors but did not look at how smaller scale decisions and investments could impact energy costs. Chapter 3 addresses smaller scale decisions and the interactions between energy and a different sector (water) by creating a more granular optimization model. We create a mixed-integer linear program for the optimal system design and dispatch of both the energy and water systems using data from a neighborhood in Austin, Texas. Using this model, we assess the ability of two system design concepts to improve the economics of distributed water and energy technologies, and ultimately encourage their broader adoption: (1) co-optimizing water and energy technology investments and operations, and (2) investing in community-scale rather than home-scale systems. Our results show that distributed electricity and water production increases, and total cost decreases, when resources and demands are pooled at larger community scales. Furthermore, the cost and carbon emissions reduction benefits of co-optimizing distributed water and energy investments are significant, especially at higher aggregation levels. These community-scale systems make a wider range of technologies economically viable and enable greater asset utilization due to systems integration.

The project in Chapter 3 explored how distributed water and energy technologies could meet residential demand and Chapter 4 expands this assessment into the agricultural space. The project in this chapter investigates how a farm can use distributed energy and water technologies to mitigate the effects of intensifying water scarcity due to climate change and unsustainable withdrawals from conventional freshwater sources. It creates a two stage quadratically constrained linear programming framework to provide insights. Our results show that expected profit and realized profit are heavily dependent on a decision maker's given climate probabilities. Aggressively preparing for an extreme climate can cause significant losses if a more moderate climate is realized. Furthermore, year-to-year weather variability within a given climate scenario can also diminish the potential cost savings from investing in alternative resources. The framework we created in this work can help decision makers evaluate those uncertainties, decide to invest in alternative water and energy technologies, and how to appropriately size those investments given climate uncertainty.

The three projects of this dissertation use a multi-system framework and employ operations research methods to model how investigating the community scale and integrating the design and operation of energy supply and end-use systems can lead to mutually reinforcing benefits. Each project offers insights on how a multi-system framework can improve emerging technology adoption, reduce GHG emissions, and/or lower individual costs. These insights can be used by decision makers to help create a more efficient and sustainable world.

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Chapter 1

Introduction

The decarbonization, decentralization, and digitization of the energy sector provide many opportunities in numerous sectors, but also introduce complexities and idiosyncrasies that must be properly managed. These three "Ds" have the potential to disrupt every field but have a particular effect on the energy sector as policies encourage decarbonization and the adoption of renewable energy resources, increased customer demand requires decentralization, and digitization creates new ways to exchange goods and services (Di Silvestre et al., 2018; Infosys Insights, 2016). Global energy demand is expected to plateau after 2035 as the energy intensity of economies and the penetration of renewable energy sources increase efficiencies, but electricity consumption is predicted to double by 2050 as electrification across end uses like buildings and transportation expands (McKinsey, 2019). These trends have the potential to transform the grid edge as technologies like electric vehicles, heat pumps, distributed storage, and networking technologies are integrated in the new grid. And these technologies have the potential to decrease costs, create innovative customer centric business models, and improve the asset utilization rate of the electricity system (World Economic Forum and Bain and Company, 2017).

Technologies that run on electricity rather than fossil fuels not only have lower carbon intensities, but are also generally more efficient and have lower energy intensities, thus electrification is a key factor in decarbonization especially when paired with increasing renewable electricity generation (Griffith et al., 2020). Yet, electricity provides less than half of the final energy used and the direct use of fossil fuels usually by burning satisfies the plurality of energy demand (Jadun et al., 2017). The scale of electrification might follow historical S-curve adoption patterns of other technologies and which would imply an increase of electric vehicles and electric heat pumps that would increase electricity demand and change the electric load shape (Mai et al., 2018). Any change in electric load shape requires better demand data and modeling so that generation sources can adjust and adapt to the new paradigms (Jadun et al., 2017; Sun et al., 2020). Digitization of the grid can help with this process and create new opportunities for efficiencies, energy products, and cost savings.

Digitization and renewables have created opportunities to streamline business processes, monitor energy efficiency, and provide cost-effective energy. And as more end-use sectors like transportation, water, buildings, and agriculture electrify the effects of digitization extend beyond the energy sector and enable opportunities in smart demand response, the integration of variable renewable energy sources, the smart charging of EVs, and distributed electricity resources (DERs) (IEA, 2017). Therefore, while the interdependencies of these systems create new complexities and challenges, they can also provide opportunities. However, finding these synergies requires systems of systems thinking and techniques like integrated assessment modeling (Keating et al., 2003; Nordhaus, 2013).

Electrification integrates many different systems with the energy sector, which increases efficiency but also creates new vulnerabilities that can cause cascading failures emanating from a single failure in the energy system. Digitization which includes smart metering and controls can provide information that can produce higher quality decisions. These new digital devices can affect the power sector by providing the ability to optimally control loads, but since they can also fail because of lack of power, systems malfunctions, or unauthorized access, they too can cause cascading failures. Decentralization tempers against the risk of cascading failures but the costs are shouldered by individuals and communities who could end up shouldering higher amounts of risk and coordinating with the large numbers of "prosumers" can create immense operational complexity (Xu and Po, 2019).

Nonetheless, if these systems are optimized with the power sector, it could help incorporate and accelerate the integration of intermittent renewables cost effectively. On the other hand, if they are optimized with respect to factors like resilience or convenience, they could place addition burdens on the power sector, making certain transitions harder. Being able to choose what to optimize and then balancing the needs of each system is essential in these multi-system optimization problems. Optimizing one system and ignoring others might not only be suboptimal for the combined group of systems but also for the system that you are optimizing. There are potential co-benefits to systems integration that can be realized with multi-systems optimization. This dissertation explores the interconnections between the electricity, transportation, water, and agricultural systems and develops scenarios and optimization schemes to explore the co-benefits of integrating these systems.

Therefore, this dissertation examines the investment and operational decisions different systems must make in coordination with the power sector and other relevant systems. The projects in this dissertation explore decarbonization pathways like electrification, investigate the effects of decentralization, and rely on the information provided by digitization. This dissertation uses systems of systems thinking and multi-systems optimization techniques like integrated assessment modeling to explore these multi-systems problems. The rest of the dissertation consists of the following studies.

1.1 Co-optimization and community: Maximizing the benefits of distributed electricity and water technologies

The first main chapter of this dissertation develops an optimization model combining the power and transportation sectors for the City of Austin using an integrated assessment model framework. This macro scale model allowed us to explore how the electrification of transportation and the varying flexibility of electric vehicle charging would affect the evolution of the power sector and vice versa. Although this model did not explore the effect of decentralization and only explored the implications of digitization in the form of a new shared autonomous transportation future, it provided valuable insights into how decarbonization in the form of intermittent renewables and the electrification of transportation could create new interdependencies and integrated effects. Even as a relatively straightforward top-down model it provided the following key insights.

1) SAVs lower costs and carbon emissions, even if they induce significant additional VMT
2) The transition to SAVs accelerates vehicle electrification
3) Synchronizing electric SAV charging with renewable power output has large benefits

1.2 Co-optimization and community

The second main chapter of this dissertation develops a multi-systems optimization model that investigates individual and community level decisions and the synergies between investing in distributed energy and water technologies. Modeling at this scale allows us to explore how individual and community level (i.e. decentralized) investment decisions could affect the operation of energy and water systems. Furthermore, this model investigates how investing in energy and water systems together affects both the investment and operation decisions of both systems for the better. The key insights this modeling approach provides are listed below.

1) Distributed Energy and Water Technologies are economically competitive at today's prices, especially when they are co-optimized
2) The electricity or water produced by distributed technologies generally increases with aggregation level because as more houses pool their resources they can afford to buy more efficient technologies

3) Because the model is backstopped by the utilities there is a maximum "budget" that can be spent on distributed technologies and co-optimized systems do this more efficiently
4) Co-optimizing balances the energy demand increase from Distributed Water Technologies with the carbon intensity reductions of Distributed Energy Technologies

1.3 Agricultural planning under climate uncertainty

The third main chapter of this dissertation investigates agriculture as an energy application. This work creates a stochastic framework that balances maximizing profit by balancing crop yield with water and energy costs. From an operations research perspective, this model has intriguing complexities because of the quadratic crop function that links crop yield to water provision and the requirement that an investment decision must be made before realizing the uncertain operational conditions. Once again we illustrate how distributed water and energy technologies can affect both investment and operational decisions; however, the main findings from this work deal with how climate predictions affect investment decisions and by extension farm profit. Aggressive predictions can lead to heavy losses if the climate goes against your predictions, losses that can be mitigated by shoring up resources via alternative sources. The insights from this framework can help agricultural decision makers determine how to address climate uncertainty and to a limited degree weather variability via investments in alternative water and electricity resources to help improve resilience and shore up profits.

1.4 Organization of the Dissertation

This chapter provided a brief introduction to the studies in this dissertation. The subsequent chapters have more detailed problem descriptions and literature reviews. The rest of the dissertation is organized as follows. Chapter 2 investigates the possible climate change impacts of the anticipated growth in shared autonomous vehicles (SAVs) by creating an optimization model based on OSeMOSYS. Chapter 3 addresses smaller scale decisions and the impact of energy on a different sector (water) by creating a mixed-integer linear program for the optimal system design and dispatch of both the energy and water systems using data from a neighborhood in Austin, Texas. Chapter 4 investigates how climate uncertainty affects a farm's decision to invest in alternative electricity and water technologies in a resource constrained environment. It creates a framework to compare how a decisions makers climate predictions impact profit and investment decisions in various possible climate realizations to help them consider climate uncertainty and how to mitigate its impacts.

Chapter 2

Contributions of shared autonomous vehicles to climate change mitigation

2.1 Introduction

[1] On-demand mobility and vehicle automation are expected to grow rapidly over the coming decades. 15% of Americans used an on-demand mobility service in 2016 (Smith, 2016), and Navigant Consulting projects that 75% of new light-duty vehicles will be automated by 2035 (Navigant Consulting Inc, 2015). On-demand mobility and automation, especially in their combined manifestation as shared autonomous vehicles (SAVs), could have major implications for car ownership, congestion, vehicle miles traveled (VMT), traffic safety, urban form, and environmental impacts. The consequences of widespread SAV adoption for climate change mitigation are highly uncertain due to competing mechanisms whose mangitudes are difficult to estimate. SAVs could decrease greenhouse gas (GHG) emissions by improving fuel efficiency, alleviating congestion, facilitating the diffusion of alternative fuel vehicles (AFVs), matching vehicle sizes to trip requirements, reducing parking needs, and other factors (Greenblatt and Saxena, 2015; Wadud et al., 2016). On the other hand, SAVs could increase GHG emissions by reducing the cost of travel (thus leading to a rebound effect that increases VMT), allowing non-drivers to travel more by car, and accumulating more miles without any passengers in the vehicles (Anderson et al., 2014). As an indicator

[1]This work has been previously published where I contributed to the design of the model, interpreted the results, created the graphics, and wrote the text of the paper. Citation: Jones, Erick C., and Benjamin D. Leibowicz. 2019. "Contributions of Shared Autonomous Vehicles to Climate Change Mitigation." Transportation Research Part D: Transport and Environment 72: 279–98.

of the uncertainty in these mechanisms, experts contend that autonomous vehicles could plausibly cut road transport GHG emissions in half, or double them, depending on which effects dominate (Wadud et al., 2016).

To explore the potential roles of SAVs in climate change mitigation pathways, we develop an energy system optimization model with integrated electricity and transport sectors that distinguishes SAVs from privately owned vehicles (POVs). While several previous studies have modeled SAV fleet operations in considerable detail and estimated environmental outcomes (Chen et al., 2016; Fagnant and Kockelman, 2014), these analyses were based on exogenously specified vehicle fleets and did not consider interactions between the vehicles and the broader energy system. By contrast, our energy system optimization model features endogenous vehicle technology adoption, allowing it to capture the effects of SAV uptake on the mix of vehicle technologies in the fleet. In addition, the model optimizes electricity generation investments alongside the vehicle fleet, so that generation profiles can be aligned with electric vehicle charging as much as possible. This integration of electricity and transport sectors captures the value of coordinated charging schedules that would be easier to implement with SAVs than with POVs. We run and compare a total of ten "what-if" scenarios distinguished by SAV diffusion profiles, carbon policies, electric SAV charging paradigms, and responses of VMT to SAV diffusion.

To preview our key findings, results show that a system with significant SAV adoption is less costly and produces less GHG emissions than one with only POVs. Interestingly, these outcomes continue to be true even if SAVs induce double the VMT of the POVs they replace. The cost and emissions advantages of SAVs increase if electric SAV charging can be optimally scheduled throughout the day rather than limited to taking place only at night. The electricity generation mix can be expected to shift toward solar power, which is only available during the daytime. Aligning electric SAV charging with the solar generation profile increases the utilization of cheap, clean electricity, and reduces investments in battery electricity storage needed to balance intermittent renewables. However, we do not find evidence for meaningful impacts of SAV adoption on the electricity generation mix, even if electric SAV charging can be optimized to facilitate the integration of intermittent resources, in principle.

The remainder of this article is structured as follows. Section 2.2 reviews the most relevant literature on transport sector emissions, model-based decarbonization pathways, on-demand mobility, and autonomous vehicles. Section 2.3 describes the methodology including our model and data sources. We outline the ten scenarios that we run and compare in Section 2.4. Section 2.5 presents and discusses the scenario results. We conclude in Section 2.6 with a summary of our most important findings, acknolwedgment of limitations, and directions for future research.

2.2 Literature review

2.2.1 Transport sector emissions

Transportation recently surpassed electricity generation as the top GHG emitter in the U.S. Transportation accounts for nearly 28.5% of U.S. emissions and has the fastest-growing emissions of any energy end-use sector (Bloomberg New Energy Finance, 2018; EPA, 2017). The transport sector is also the fastest-growing source of GHG emissions globally, where it accounts for 24% of emissions (IEA, 2018). Passenger cars are responsible for 60% and 75% of transportation emissions in the U.S. and around the world, respectively (EPA, 2017; IEA, 2018). These statistics make it clear that decarbonizing the transport sector, especially light-duty vehicles, must necessarily be a major piece of any meaningful, large-scale climate change mitigation effort. However, internal combustion engine vehicles (ICEVs) fueled by gasoline are considered one of the most difficult and expensive components of present energy systems to replace with more environmentally sustainable alternatives. They are locked-in by numerous and powerful technological, infrastructural, and behavioral factors that favor the persistence of the status quo in transportation (Seto et al., 2016).

Extensively decarbonizing the transport sector will require a shift away from ICEVs to alternative technologies such as hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), battery electric vehicles (BEVs), and hydrogen fuel cell vehicles (HFCVs). However, to varying degrees, these technologies must overcome a wide variety of barriers to adoption. Depending on the technology, frequently cited barriers include high costs, inferior performance, limited range, fuel storage challenges, safety risks, undervaluation of environmental performance, insufficient supporting industries, and a lack of required infrastructure (Brooker et al., 2010; Chen et al., 2016; Leibowicz, 2018; Sierzchula et al., 2014). However, ridesharing and automation could make some of these barriers to adoption easier to overcome. For example, technologies with high upfront costs but low variable costs would be favorable for shared vehicles with high annual mileage, and autonomous vehicles could seek refueling or charging without inconveniencing passengers.

2.2.2 Model-based decarbonization pathways

Energy system optimization models such as MARKAL/TIMES (Loulou et al., 2004), MESSAGE (Leibowicz et al., 2016), and OSeMOSYS (Howells et al., 2011) determine the most cost-effective sets of technology capacity investments and operational schedules over time that satisfy demands for energy resources and services. By varying technological, economic, and policy input assumptions, these models can elucidate a range of plausible energy and environmental futures to guide energy strategy and policy formulation. Other energy-economy models like GCAM (McJeon et al., 2011), MESSAGE-MACRO (Messner and Schrattenholzer, 2000), and IMAGE (Stehfest et al., 2014) have partial or general equilibrium structures and are solved as recursive dynamic simulations rather than intertemporal optimization problems. Nevertheless, they are similarly used to evaluate climate change mitigation policies and strategies. Given the importance of the transport sector for GHG emissions, energy-economy models have expanded from their traditional supply-side focuses to incorporate richer representations of light-duty vehicles. While the modeling literature has paid scant attention to on-demand mobility and automation, many studies have assessed the interactions between climate policy and the evolving technology and fuel mixes in the passenger car fleet (Edelenbosch et al., 2017).

Karkatsoulis et al. (2017) used a transport-oriented version of the GEM-E3 general equilibrium model to investigate transitions toward low-carbon transportation in the European Union through 2050. Their decarbonization scenario projects that HEVs, PHEVs, and BEVs will combine to take over a majority of the passenger car stock by 2040. McCollum et al. (2017) developed a MESSAGE-Transport variant of the MESSAGE energy system optimization model and found that gasoline cars would be replaced by a more diverse mix of AFVs. In addition to EVs, the fleet would also shift to incorporate vehicles fueled by biofuels and synfuels. The more the model was configured to account for consumer behavior, the more that vehicles powered by alternative liquid fuels (as opposed to electric options) came to dominate the post-gasoline vehicle fleet. Longden (2014) explored the effects of climate policy on the optimal vehicle fleet using the WITCH model. He found that even modest emissions reduction goals stimulate large investments in HEVs, PHEVs, and BEVs, but that cost reductions and the removal of barriers to adoption will be required to support substantial increases in the shares of these vehicle types. Sano et al. (2015) used the DNE21+ model and found that the 2050 passenger car mix is very sensitive to the stringency of the climate policy target. Under a 550 parts per million carbon dioxide equivalent (ppm CO_2eq) target, gasoline ICEVs retain a majority of the fleet in 2050, with only HEVs making notable inroads. Under a more ambitious 450 ppm CO_2eq target, ICEVs are almost entirely replaced by a diverse mix of HEVs, PHEVs, BEVs, and HFCVs.

The IEA (2012), employing their custom optimization model ETP-TIMES, determined that HEVs, BEVs, and HFCVs would be cost-competitive with gasoline- and diesel-powered vehicles under a restrictive carbon policy. Fulton et al. (2015) extended the ETP-TIMES framework and projected that gasoline- and diesel-powered vehicles will be completely replaced by HEVs, BEVs, and HFCVs by 2075. Yin et al. (2015) used the GCAM model to investigate the future Chinese transport sector. In their reference scenario without carbon policy, the results indicate that oil liquids will continue to dominate the ground transportation energy mix in 2095. Even under a variety of CO_2 mitigation trajectories, oil liquids account for the greatest share of transportation energy use through at least 2050. Only the most stringent decarbonization goal considered causes biofuels, electricity, and hydrogen to combine for more than half of the 2095 transportation energy mix.

As the paragraphs above demonstrate, energy-economy models have been used extensively to analyze the interactions between climate change mitigation and the mixes of vehicle technologies and fuels in the light-duty fleet. However, they have not been used to assess the role of SAVs in decarbonization pathways, likely because the distinction between SAVs and POVs is less clearly compatible with the model structures than the distinctions between vehicle types that consume different fuels or represent varying capital cost versus efficiency tradeoffs. Our study addresses this gap in the modeling literature by incorporating SAVs into an energy system optimization framework to explore their implications for system-wide GHG abatement.

2.2.3 On-demand mobility

On-demand mobility is the class of transportation services that encompasses both carsharing (e.g., Zipcar, car2go) and ridesharing (e.g., Uber, Lyft). Carsharing customers receive the benefits of on-demand access to a vehicle without directly incurring the costs of ownership. The shared car is retrieved from a specified origin, used, and then returned to a designated location or to any location within a designated area. As of 2016, North America had over 1.8 million carsharing members and over 26,000 shared vehicles available to rent

(Shaheen et al., 2018). Ridesharing services, on the other hand, connect passengers with drivers of personal vehicles ready to transport them for a fee. The service, usually through a smartphone app, electronically handles the booking, payment, and rating systems for drivers and passengers. Ridesharing services are growing very rapidly. The number of Uber driver-partners expanded from near zero in 2012 to over 150,000 in 2015 (Hall and Krueger, 2015). Uber reached the 2 billion ride milestone in 2016, followed by the 5 billion ride milestone in 2017, and actually provided 4 billion rides in 2017 alone (Bhuiyan, 2018).

Carsharing has been shown to reduce GHG emissions by causing high-mileage users to lower their mileage more than carless or low-mileage users increase their mileage. In fact, in 2009 when there were only 378,000 carsharing members in North America, the survey-based model constructed by Martin and Shaheen (2011) suggested that ridesharing reduced GHG emissions by up to 155,000 tons per year. Ridesharing services have been found to have much higher average occupancy rates than regular taxis (1.8 people vs. 1.1 people) which reduces GHG emissions as well (Greenblatt and Shaheen, 2015). Another study discovered that 15% of Americans used a ridesharing service in 2016, and that ridesharing customers are less likely to own a car (Smith, 2016).

However, survey results obtained and analyzed by Clewlow and Mishra (2017) suggest that ridesharing services are likely to increase VMT in U.S. cities by replacing trips on public transit with more VMT intensive ridesharing trips and encouraging users to take trips that they otherwise would not have. Interestingly, the survey does not support the assumption that ridesharing lowers car ownership rates. Furthermore, Henao and Marshall (2018) shows that ride-hailing adds a significant amount of VMT to the system when accounting for deadheading, induced travel, and substitution of more sustainable modes. Deadheading (i.e. driving without a passenger), accounts for the majority of the additional VMT. In conclusion, carsharing has been shown to reduce personal VMT and ridesharing has been shown to increase occupancy rates, but ridesharing has also been shown to cannibalize public transit and increase total VMT. Given the contrasting findings and large uncertainty surrounding VMT impacts, in this study we analyze and compare scenarios in which SAV diffusion lowers, has no effect on, or raises VMT."

2.2.4 Vehicle automation

Autonomous vehicles are vehicles that move passengers or cargo without any human intervention. Full automation technology is still in its infancy, but partial automation exists to varying degrees. The Society of Automotive Engineering and the National Highway Transportation Safety Administration define five levels of vehicle autonomy from Level 0 (no automation) to Level 5 (full automation) (NHTSA, 2018; SAE International, 2019). For the purposes of our study, the representation of SAVs in the model is consistent with automation Level 4 and above.

Autonomous passenger vehicles have the potential to make vehicles safer, more efficient, and allow passengers to focus on other tasks in transit; they also will dramatically affect traffic, vehicle mileage, and emissions (Fagnant and Kockelman, 2015). Mass adoption of autonomous vehicles depends on a wide variety of factors including law, policy, perceived safety, and costs (Fagnant and Kockelman, 2015). However, vehicle automation is expected to expand rapidly. Navigant Consulting predicts that 75% of new light-duty vehicles will be autonomous by 2035 (Navigant Consulting Inc, 2015).

Optimized braking and acceleration (eco-driving), as well as fast reaction times that enable the use of "platooning," could allow autonomous vehicles to realize superior fuel efficiency (Wadud et al., 2016). Furthermore, autonomous vehicles are expected to have the ability to communicate with each other, which would enable congestion mitigation, the ability to continuously optimize routes, and coordinated platooning for even more dramatic efficiency gains (Anderson et al., 2014). Other studies show that a SAV could replace up to ten POVs, so a SAV that is more environmentally friendly than the POVs it replaces, even if it drives more miles, should have a positive environmental impact (Fagnant and Kockelman, 2014).

On the other hand, by increasing driving speeds, optimized routes and traffic avoidance could have the unintended effect of lowering fuel efficiency (Wadud et al., 2016). More importantly, autonomous vehicles might reduce the time cost of travel by allowing passengers to engage in other activities while on the road. This reduction in travel cost would be expected to induce more VMT, thus producing more GHG emissions (Anderson et al., 2014). Studies suggest that additional mileage from people who previously were not able to drive (e.g., children, the elderly, persons with disabilities) could offset efficiency improvements and make automation a net environmental negative, despite providing valuable transportation service to these groups (Anderson et al., 2014; Brown, 2018).

2.2.5 Shared autonomous vehicles

Automation can complement on-demand mobility by having autonomous vehicles drive to users (shortening wait times), park themselves, and refuel or recharge on their own (Greenblatt and Shaheen, 2015). Waymo and Uber are running SAV trials in Phoenix, Arizona (Lee, 2017), and Google and Europe's CityMobil2 are currently running SAV pilot projects. Although these autonomous vehicles currently have some limitations, it can be assumed they will soon be able to do anything a normal vehicle can do (Fagnant and Kockelman, 2018). Furthermore, a study carried out by Fulton et al. (2017) showed that implementing automation without ridesharing would diminish its benefits, especially for the environment. Ridesharing and autonomous vehicles are naturally complementary in many respects, and the two technologies will likely mutually enhance one another. Therefore, in this study we consider a future transport sector with substantial adoption of SAVs rather than consider ridesharing or autonomous vehicles individually.

Researchers have developed a number of temporally and spatially detailed agent-based models to simulate SAV fleet operations (Berrada and Leurent, 2017). These models have been used to examine the environmental impacts of SAVs versus POVs assuming a simple refueling process (Fagnant and Kockelman, 2014), and subsequently with a sharper focus on EV charging (Chen et al., 2016). In their simulation of SAV fleet operations in Austin, Texas, Fagnant and Kockelman (2014) projected that one SAV could replace 11 POVs and have a beneficial overall effect on the environment. While these agent-based models can be used to estimate certain performance and environmental outcomes, they make exogenous assumptions about the vehicle technology mix and do not capture interactions between vehicles and the broader energy system. The present study serves to address these gaps in the literature.

2.3 Methodology

2.3.1 Open Source Energy Modeling System (OSeMOSYS)

The model we develop for this study is based on the Open Source Energy Modeling System (OSeMOSYS). OSeMOSYS is an energy system optimization framework structured as a deterministic linear program that minimizes net present costs by endogenously deciding what technologies satisfy exogenously determined demands for every specified time period while operating within a host of constraints (Gardumi et al., 2018; Howells et al., 2011). It is similar in structure to energy modeling platforms like MARKAL/TIMES (Loulou et al., 2004) and MESSAGE (Leibowicz et al., 2016), but the OSeMOSYS code is open source to promote research transparency and enable customization. OSeMOSYS is highly flexible, modular, and can be tailored to a wide array of energy applications by constructing appropriate input databases. Example applications of OSeMOSYS in the recent literature include analyses of cross-border electricity trade in South America (de Moura et al., 2018), electricity capacity planning strategies under climate policy uncertainty (Leibowicz, 2018), integration of techno-economic and behavioral end-use technology adoption models

(Fragnière et al., 2017), and optimal decarbonization pathways for power and transportation at the urban scale (Brozynski and Leibowicz, 2018).

Tailoring OSeMOSYS to a particular application requires the construction of a database that includes sets of technologies, demands, energy resources, carbon and energy intensities, efficiencies, model periods, and timeslices. Model periods represent the time step of the analysis (e.g., annual) and span the model timeframe (e.g., present through 2050). Timeslices allow for a simplified computation of system operations (i.e., dispatch) within each model period, which is important for capturing resource intermittency, time-varying demand levels, and energy storage operations. We describe our OSeMOSYS implementation and database in the following subsections. Since the standard OSeMOSYS framework has been well documented elsewhere, we focus on the unique aspects of our model and database, especially those introduced to incorporate SAVs. For further information about OSeMOSYS, please refer to the original documentation by Howells et al. (2011) and the OSeMOSYS website (www.osemosys.org).

2.3.2 Model implementation and customization

We develop a General Algebraic Modeling System (GAMS) implementation of OSeMOSYS, along with a database for Austin, Texas, that are extensions of the code and database previously constructed by Brozynski and Leibowicz (2018).[2] In their study, Austin was used as a test case for evaluating optimal decarbonization pathways for power and transportation at the urban scale. Austin was – and remains – a valuable testbed for analysis due to its prominent role in the C40 Cities Climate Leadership Group (C40 Cities, 2018) committed to limiting global warming to 1.5°C, and its particularly ambitious, enacted goal of achieving net-zero citywide GHG emissions by 2050 (City of Austin, 2015). In addition,

[2]Noble (2012) provided the first translation of OSeMOSYS into GAMS, and subsequent GAMS implementations have built on that one.

previous agent-based simulations of SAV fleet operations have been carried out for Austin (Chen et al., 2016; Fagnant and Kockelman, 2014), and they provide valuable place-specific data inputs for our case study. The Austin municipal government has authority over local transportation planning and also directs Austin Energy, which is the ninth largest publicly owned electric utility in the U.S. (Austin Energy, 2018). This integrated control of the power and transportation sectors is consistent with the OSeMOSYS structure, in which a single optimizing agent solves an intertemporal optimization problem. In this study, we extend the OSeMOSYS model and Austin database to incorporate SAVs, and explore their roles in climate change mitigation pathways.

Even before incorporating SAVs, our OSeMOSYS implementation includes several structural modifications and additions that distinguish it from the standard version. These structural components are introduced to integrate the transport sector into the OSeMOSYS framework, since the standard model structure corresponds to energy supply systems and must be modified to accommodate end-use technologies. First, we make POVs non-dispatchable. Unlike power plants, they cannot be dispatched in ascending order of marginal cost until demand is satisfied, because POVs are driven by individual owners rather than centrally coordinated. For example, in a given timeslice with relatively low demand for private VMT, there is no reason to believe that only the lowest marginal cost vehicles (e.g., HEVs, BEVs) will be used, while higher marginal cost vehicles (e.g., ICEVs) remain idle. To make POVs non-dispatchable, we constrain the shares of vehicle types operating in every timeslice to be equal to their capacity shares of the POV fleet. Second, we introduce a sophisticated formulation of EV charging and vehicle-to-grid (V2G) capabilities. This formulation ensures that charging, discharging (V2G), driving, and sitting idle are mutually exclusive activities on the vehicle and timeslice level. Third, we constrain annual capacity growth rates by technology to prevent unreasonably rapid scale-up trajectories. These constraints are endogenous in that the allowable new capacity in one model period depends on the total capacity in the previous period. Similar endogenous constraints are featured in many energy-economy models to prevent the optimization scheme from yielding "bang-bang solutions" with unrealistic technology substitution dynamics (Craxton et al., 2017; Iyer et al., 2015; Leibowicz et al., 2016; Wilkerson et al., 2015), but they are not included in the standard version of OSeMOSYS.

We incorporate SAVs into the OSeMOSYS transport sector by creating two distinct transportation demands, one satisfied by POVs, and another satisfied by SAVs. The model database includes a POV variant and an SAV variant of each represented vehicle technology: ICEVs, DIESEL, HEVs, PHEVs, BEVs, and HFCVs. There is an exogenous electricity demand that grows over time and reflects all non-transportation end-uses of electricity. Endogenous electricity demand arising from the model's deployment of EVs is added to the exogenous load profile. Therefore, the model considers the temporal relationships among exogenous electricity demand, additional demand due to EV charging, and the generation profiles of various electricity supply technologies. This full integration of the electricity and transport sectors has been missing from the previous literature on SAVs.

2.3.3 Distinctions between SAVs and POVs

In this subsection, we outline the structural and parametric distinctions between POVs and SAVs that capture their key differences in the model. Table 2.1 provides a succinct overview of these distinctions. Given that ridesharing and vehicle automation are relatively immature technologies, we emphasize that some of our parameter value assumptions are ad hoc estimates that do not reflect empirical data, as the historical record is very limited.

2.3.3.1 Capital cost

Researchers predict that autonmous vehicle technology will add a premium of \$7,500 – \$10,000 to the cost of a vehicle when an autonomous version first becomes commercially available. However, this premium will likely have to decline toward $1,000 for autonomous vehicles to be adopted at scale (IHS Automotive, 2014). LIDAR sensors such as Waymo and Velodyne's Puck cost around $7,500 today but other companies have promised sensors between $100 and $250 in the future (EIA, 2017). We initially set the capital cost of each SAV technology in the base year to $7,500 above the cost of the corresponding POV technology, and reduce this SAV cost premium linearly over time until it reaches $1,000 in 2030. It remains constant thereafter.

2.3.3.2 Efficiency

We parameterize each SAV technology to have 10% higher fuel efficiency than its corresponding POV variant. Some researchers have predicted that autonomous vehicles will be up to 80% more efficient than conventional vehicles (Morrow et al., 2014), but other predictions are more conservative and go down to as low as a 4.5% efficiency improvement (EIA, 2017). Our assumption that SAVs have 10% higher fuel efficiency than POVs should be interpreted as a relatively conservative estimate. Within the model, this single efficiency distinction is introduced to reflect differences in acceleration and braking patterns, traffic avoidance, platooning, intersection maneuvering, and any other factors that affect realized fuel efficiency.

Although, autonomous vehicles have the potential to reduce traffic and increase average speeds, we did not model any dynamic changes to traffic conditions for SAVs or POVs. We used the same vehicle average speed from the (Brozynski and Leibowicz, 2018) model calculated from actual city of Austin traffic data. This should produce a conservative estimate of the average speed because even while ignoring the effect of vehicle autonomy the presence of SAVs in our scenarios will reduce the number of vehicles on the road and by extension traffic at any given time."

2.3.3.3 Operational life

The operational life of SAVs is assumed to be five years, compared to the ten year life assumed for POVs. For some context, the average New York City taxi has an operational life of 3.3 years, while the average New York City black car has a life of 5.5 years (NYC Taxi and Limousine Commission, 2014). We believe that five years is a reasonable assumption for SAVs, which should be able to run smoother and more efficiently, thus prolonging vehicle life.

2.3.3.4 Technology growth rate constraints

We allow individual vehicle technologies (e.g., BEVs, HFCVs) to expand faster within the SAV fleet than within the POV fleet, for several reasons. The former is operated as a business with centralized decision making and strong profit motives that are amenable to swifter and more decisive technology strategies, while the latter involves myriad individual decision makers choosing their own vehicles to drive. The possibility of faster vehicle technology transitions in the SAV fleet is also consistent with the assumption of shorter vehicle lifetimes, since the retirement of a vehicle marks a prime opportunity to adopt a different technology. Furthermore, a centrally coordinated SAV fleet could more easily overcome some of the barriers to adoption associated with BEVs and HFCVs, such as a lack of charging or refueling infrastructure, limited range, and long charging times. For instance, an SAV fleet of sufficient scale could install its own charging/refueling stations, assign BEVs to trips with distances in their current charge ranges, and send vehicles to charge or refuel when travel demand is low. Observationally, ridesharing companies like Uber and Lyft are enthusiastically pursuing and trialing autonomous vehicle technology, demonstrating that the profit motive is strong. As a result of all these considerations, we allow the capacity of each SAV technology to expand up to 10% annually, which is double the 5% growth rate constraint applied to POV technologies.

2.3.3.5 Other distinctions

POVs are assigned a maximum capacity factor of 10% in all timeslices, so that at most 10% of the POV fleet can be in operation, satisfying demand for private VMT, in any given hour. This value reflects empirical data indicating that only a small fraction of personal automobiles is ever in use, even at peak travel times (Federal Highway Administration, 2009). SAVs can be operating and fulfilling demand for shared VMT almost continuously, so we assign them a maximum capacity factor of 95% in all timeslices. The slight difference between this parameter value and 100% can be attributed to maintenance. Note that electric SAVs (eSAVs) that the model assigns to charge or provide V2G power in a given timeslice cannot also be in operation, so this endogenous allocation will generally mean that fewer than 95% of the SAVs are available to provide shared VMT. However, the optimization scheme can strategically charge vehicles at non-peak times so that the availability of SAVs at peak times is limited only by the 95% capacity factor. The opportunity to realize much higher capacity factors is a key motivation for the sharing economy.

Even with the 10% maximum capacity factor in all timeslices for POVs, the model could satisfy demand for private VMT using a POV fleet that is unrealistically small, but with vehicles that drive more annual miles than is typically observed. So, we constrain POVs to provide a maximum of 15,000 private VMT annually, which requires the model to invest in a POV fleet that is adequately sized relative to the demand for private VMT. We see no reason to impose an annual mileage constraint on SAVs, so their annual operation is limited only by the 95% maximum capacity factor that applies to all timeslices, and the need to charge.

As described in Section 2.3.2, our OSeMOSYS implementation makes POVs non-dispatchable. Since SAVs are centrally coordinated rather than operated by independent owners for their own use, we allow the SAV fleet to be economically dispatched. For example, suppose that the SAV fleet consists of 50% ICEVs and 50% HEVs, and that the latter have lower variable cost. Then, in an hour where shared VMT demand is low relative to the size of the SAV fleet, the model could satisfy demand at lower cost by dispatching all the HEVs before any ICEVs, rather than dispatching them in equal numbers. The ability to economically dispatch SAVs in this fashion could have significant value if shared VMT demand is sharply peaked and the SAV fleet undergoes a transition phase with a diverse mix of vehicle technologies.

2.3.4 Vehicle technology assumptions

This section briefly outlines key input parameter assumptions that are common to both POVs and SAVs. In other words, these assumptions correspond to the underlying drivetrain technologies, whether they appear as POVs or SAVs. Table 2.1 provides a succinct summary.

2.3.4.1 Efficiency improvements

We assume that the efficiencies of fossil fuel vehicles will improve by 1.48% per year, so that they reach the 39 miles per gallon (mpg) projected combined fuel efficiency for all light-duty vehicles in 2050 (EIA, 2018a). These fuel efficiency improvements are due to technological enhancements in internal combustion engines and other ancillary technologies, most of which are not incorporated into AFV technology options (EIA, 2018b). However, some portion of the projected improvements can be attributed to technologies which are also present in other vehicle types, such as tires and aerodynamic design. Therefore, we incorporate a 0.5% per year efficiency improvement for all AFV technologies.

2.3.4.2 Electric vehicle costs

Experts predict that EV battery costs will continue to decrease until BEVs eventually become cheaper to purchase than ICEVs by 2025. Battery costs have plummeted from \$800/kWh in 2011 to less than \$200/kWh as of 2018, and are predicted to fall to \$97/kWh and then \$70/kWh by 2025 and 2030, respectively (Bloomberg New Energy Finance, 2018). We assume a linear decrease in the capital cost of BEVs from \$38,886 in the base year to \$29,734 in 2025, and a subsequent linear decline to \$25,638 in 2050. Note that this assumed cost trajectory is more conservative than the \$27,000 BEV capital cost that Bloomberg New Energy Finance (2018) projects for 2025.

Table 2.1. Summary of key input parameter assumptions for POVs and SAVs.

Assumption	**Description**
SAV cost premium	Each SAV technology carries a capital cost premium relative to its corresponding POV technology due to the cost of automation equipment. This premium declines linearly from $7,500 in the base year to $1,000 in 2030, then remains constant thereafter.
SAV efficiency advantage	Each SAV technology is 10% more fuel-efficient than its corresponding POV technology. This efficiency advantage reflects finely tuned acceleration and braking patterns, traffic avoidance, platooning, intersection maneuvering, and so on.
Operational lives	All SAV technologies have operational lives of five years, while all POV technologies have operational lives of ten years. The shorter lives of SAVs reflect their far greater annual mileage.
Capacity expansion constraints	The capacity of each SAV technology can expand up to 10% per year, while the capacity of each POV technology can expand up to 5% per year. The faster allowed growth for SAVs reflects the simpler decision structure of a centrally operated, commercial fleet, where resistance to new technologies is not expected to be as strong.
Maximum capacity factors	In any timeslice, POVs have a maximum capacity factor of 10%, while SAVs have a maximum capacity factor of 95%. Only a small share of POVs is on the road at any given time, but SAVs could be in nearly continuous use.
Dispatchability	SAVs can be economically dispatched in ascending order of variable cost until demand is met, but POVs are non-dispatchable. POVs are operated by independent drivers, so the shares of POV technologies on the road in each timeslice must match their capacity shares of the POV fleet.
Fuel efficiency improvements	Fossil fuel vehicle efficiencies improve by 1.48% per year until they reach 39 mpg in 2050. AFV efficiencies improve by 0.5% per year.
BEV capital costs	BEV capital cost declines linearly from $38,886 in the base year to $29,734 in 2025, then decreases linearly again to $25,638 in 2050.

2.4 Scenarios

As mentioned in our literature review the effect of SAVs on VMT is unknown, so we explore various scenarios with differing levels of VMT demand relative to the original POV VMT demand. If the effect of SAVs on VMT becomes clearer our results can be interpolated accordingly.

The rate of SAV penetration is unknown, yet we assume 70% of VMT is met by SAVs in our SAV scenarios. In order to interpolate results for different SAV penetration rates we need a baseline to compare our SAV scenarios to, so we also run scenarios that have only POVs and no SAVs.

SAVs are likely to be operated by a central agent i.e. Uber or Lyft; however, single owners or small collectives could also own autonomous vehicles and share them when they are not using them. Central agents are likely to coordinate their charging schedules to charge during times when electricity is the cheapest, while single owners or small collectives are more likely to be restricted to only charge at night when they are not using the vehicles. Therefore, we explore scenarios under different charging regimes.

Currently, Austin is operating under no-carbon tax; however, implementing an increasing carbon tax as a way to capture the external costs of carbon has been suggested. Therefore, we explore all of our scenarios both under no-carbon tax and an increasing carbon tax.

In summary, we analyze a total of ten scenarios distinguished by their assumptions about SAV diffusion, carbon policy, the effect of SAVs on travel demand, and whether eSAV charging can be centrally coordinated by the system optimizing agent. Table 2.2 summarizes the ten scenarios, which the subsections below describe in more detail.

2.4.1 Carbon policy

Half of our scenarios do not feature a carbon policy, while the other half include a carbon tax that starts at a low level then ramps up over time. The particular carbon tax profile we implement begins at \$20 per ton of CO_2 (tCO_2) in the base year and increases by 5% annually. This trajectory, which is plotted in Figure 2.1a, reaches \$41.58/tCO_2 in 2030 and \$110.32/tCO_2 in 2050. Similar carbon tax ramps are frequently used in the literature to assess the impacts of climate policy, and our carbon tax is less stringent than the policies considered by Wilkerson et al. (2015), for example.

2.4.2 Demand for shared VMT

To elucidate the contributions of SAVs to climate change mitigation, we compare scenarios without SAVs to scenarios where SAVs gradually penetrate the light-duty vehicle mix over time. We model the substitution of shared VMT for private VMT using a classic logistic (i.e., S-shaped) diffusion curve. According to this model, adoption of a new technology is initially slow because technological challenges remain, costs are relatively high, and consumers are skeptical about its benefits. Adoption then accelerates as the technology improves and becomes less expensive, and consumers share their positive experiences using the technology with other potential adopters. Eventually, as the pool of potential adopters shrinks, market saturation causes adoption to plateau (Rogers, 2003). The logistic diffusion model has been shown to fit data on the expansions of historical transportation technologies very well (Grübler et al., 1999; Leibowicz, 2018). In our scenarios with SAVs, the replacement of private VMT by shared VMT is assumed to follow the form below, where the dependent variable $y(t)$ is the fraction of private VMT replaced by shared VMT in year t:

$$y(t) = \frac{k}{1 + e^{-b(t-\tau)}}. \tag{2.1}$$

The diffusion curve in Eq. (2.1) features three parameters. The parameter k is the maximum extent of diffusion, or the value that $y(t)$ approaches as the market saturates and adoption plateaus. We set $k = 0.7$ to analyze a scenario where nearly 70% of private VMT are eventually replaced by shared VMT, a transportation future in which SAVs are the dominant mode of vehicle travel. The parameter τ is the year when the diffusion curve passes through its inflection point, adoption occurs at its highest rate, and diffusion reaches half of its maximum extent (i.e., $y(\tau) = k/2$). In our parameterization, we specify $\tau = 2025$. The parameter b controls the steepness of the diffusion curve, or how gradually the adoption process proceeds. We set $b = 0.19$, which results in shared VMT expanding from replacing 7% of private VMT to 63% of private VMT over a period of 23 years. This diffusion trajectory is illustrated in Figure 2.1b.

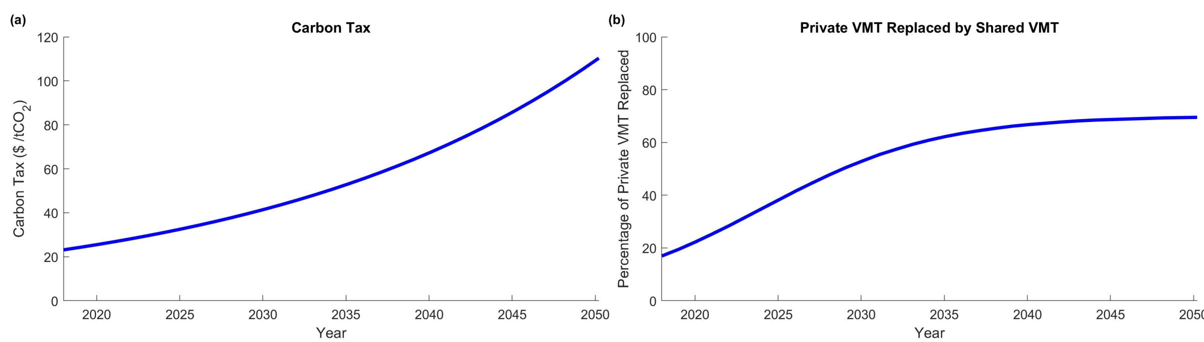

Figure 2.1. All scenarios with carbon policy feature the carbon tax profile plotted in (a). All scenarios with SAVs feature the shared VMT expansion trajectory plotted in (b).

After Eq. (2.1) has been used to determine the fraction of private VMT replaced by shared VMT in each year, the shared VMT demand is multiplied by a coefficient to allow the transition to SAVs to induce more, or less, total vehicle travel. We analyze scenarios where the shared VMT multiplier is 0.5, 1.0, or 2.0. In these scenarios, each private VMT replaced by shared VMT gets converted into 0.5, 1.0, and 2.0 shared VMT, respectively. We emphasize that these effects of SAVs on travel demand are hypothetical, and we do not make any claims about the relative likelihoods of these travel demand outcomes. The goal is to use scenario analysis to explore how the economic and environmental impacts of SAVs depend on their effect on travel demand.

2.4.3 Electric SAV charging coordination

A potential benefit of SAVs that we wish to examine through our scenario analysis is that the charging of eSAVs would be easier to centrally coordinate than the charging of electric POVs (ePOVs), because we envision the former being operated as large, commercial fleets. SAV transportation could thus provide an opportunity to make vehicle travel cheaper, help integrate intermittent renewables into the power sector, and reduce carbon emissions by aligning eSAV charging with the availability of low-cost renewable electricity. Therefore, we consider scenarios with two different eSAV charging paradigms. In one scenario variant, eSAVs and ePOVs can only charge at night, defined as the hours between 6 PM and 6 AM. In the other scenario variant, ePOVs can still only charge at night (i.e., when individuals have returned home with their vehicles), but eSAVs are allowed to charge at any time of day.[3] In reality, it is possible that smart technologies could allow for some central coordination of ePOV charging in the future, and appropriate pricing and mechanisms would need to be in place to encourage SAV fleet operators to align their charging with electricity generation to achieve system-wide optimality. Nevertheless, a transition to SAVs should make it easier to coordinate EV charging, so we design our scenarios to account for the resulting benefits.

2.5 Results and discussion

In this section we present, compare, and discuss results from the ten scenarios. We begin by examining the optimal evolutions of the technology mixes in transportation and

[3] The charging schedule is constrained endogenously by the need for some of these vehicles to be on the road satisfying demand during each timeslice. Vehicles called into service cannot also be charging.

electricity. Then, we show how carbon intensities change over time in both sectors. Finally, we investigate how total system costs vary with assumptions about SAV diffusion, carbon policy, the effect of SAVs on travel demand, and the eSAV charging paradigm. Given the vast scope of the model output, we focus on reporting and interpreting results of particular relevance to the economic and environmental impacts of SAVs rather than attempting to characterize all outcomes of all scenarios.

2.5.1 Transportation technologies

Figure 2.2 illustrates the evolution of the SAV technology mix in four scenarios distinguished by whether there is a carbon tax, and whether eSAV charging can be optimized

Table 2.2. Summary of the ten scenarios we analyze, which are distinguished by their assumptions about SAV diffusion, carbon policy, the effect of SAVs on travel demand, and whether eSAV charging can be centrally coordinated by the system optimizing agent.

Scenario	SAV Diffusion	Carbon Tax	SAV Charging	Demand Multi-plier
1	70% by 2050	No Carbon Tax	Optimized	0.5
2	70% by 2050	No Carbon Tax	Optimized	2
3	70% by 2050	No Carbon Tax	Optimized	1
4	70% by 2050	No Carbon Tax	Night Only	1
5	None	No Carbon Tax	N/A	N/A
6	70% by 2050	Carbon Tax	Optimized	0.5
7	70% by 2050	Carbon Tax	Optimized	2
8	70% by 2050	Carbon Tax	Optimized	1
9	70% by 2050	Carbon Tax	Night Only	1
10	None	Carbon Tax	N/A	N/A

or must occur during the night. Each depicted scenario assumes that shared VMT expand to replace 70% of private VMT, with a replacement rate of 1.0 (i.e., SAVs have no effect on travel demand). These results provide striking confirmation that SAVs, with their high annual mileage, constitute a favorable adoption segment for AFV technologies such as HEVs and BEVs. In all four scenarios, BEVs expand to account for more than half of the SAV fleet by 2030. The transition from ICEVs to HEVs and BEVs begins immediately and is completed in the lifetime of the initial SAV fleet. This rapid shift from ICEVs toward more environmentally friendly vehicle technologies in the SAV fleet can be contrasted with the much more gradual substitution of BEVs for ICEVs in the POV fleet, which is shown in Figure 2.3.

Interestingly, the speed and extent of the electrification trend appears to be more strongly driven by the eSAV charging paradigm than by the carbon policy, although the interaction between the two does matter. With charging confined to nighttime hours, the transition away from ICEVs first entails a shift to HEVs (with a few PHEVs), and then eventually to BEVs. HEVs actually make a comeback toward the end of the timeframe, especially if there is no carbon tax in place to penalize their emissions. As SAVs expand and the electricity generation mix shifts toward solar PV (see Figure 2.4), the inability to charge eSAVs during the day when solar PV is available makes providing electricity to charge these vehicles increasingly expensive. This would necessitate additional generation capacity that can operate during the night, or battery storage to use solar PV generation from the daytime to charge BEVs at night. Under these conditions, the optimization scheme instead turns to HEVs, a response which is dampened if a carbon tax is implemented. If eSAV charging can be centrally coordinated, then the transition to BEVs is swift and complete regardless of whether a carbon policy is active. Optimized charging causes the entire SAV fleet to consist of BEVs from 2030 onward.

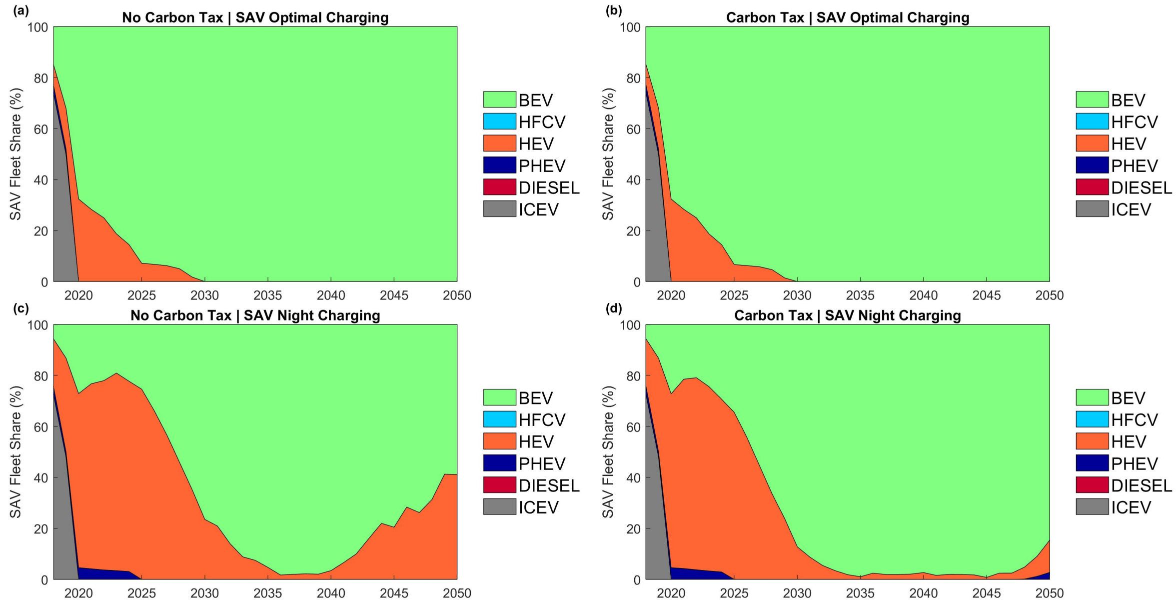

Figure 2.2. Evolution of the SAV technology mix in four scenarios distinguished by carbon policy and eSAV charging paradigm. All four scenarios assume that shared VMT ultimately replace 70% of private VMT, and that SAVs have no effect on travel demand.

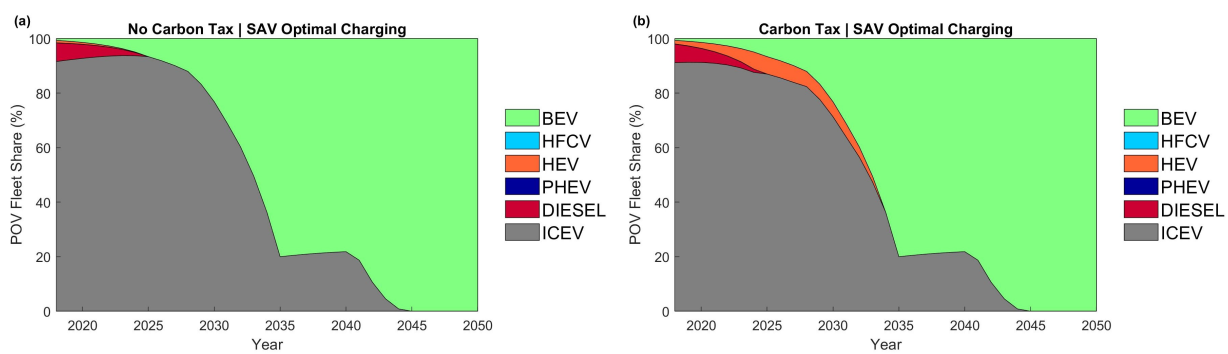

Figure 2.3. Evolution of the POV technology mix in two scenarios distinguished by carbon policy. Both scenarios assume that shared VMT ultimately replace 70% of private VMT, that SAVs have no effect on travel demand, and that eSAV charging is optimized.

2.5.2 Electricity technologies

Figure 2.4 compares the evolution of the electricity generation mix without and with the carbon tax. The two plotted sets of results both assume that shared VMT eventually replace 70% of private VMT, that SAVs have no effect on travel demand, and that eSAV charging can be optimally scheduled. We find that the carbon policy is the only scenario dimension that meaningfully affects the generation mix, so we only plot the results from two scenarios. We do not find evidence to suggest that SAV diffusion and intelligent scheduling of eSAV charging lead to cleaner electricity generation, which has previously been put forth as a supposed benefit. This finding contrasts with that of Choi et al. (2013), who determined that simultaneous adoption of EVs and coordinated charging can reduce generation capacity investments and increase the share of renewables.

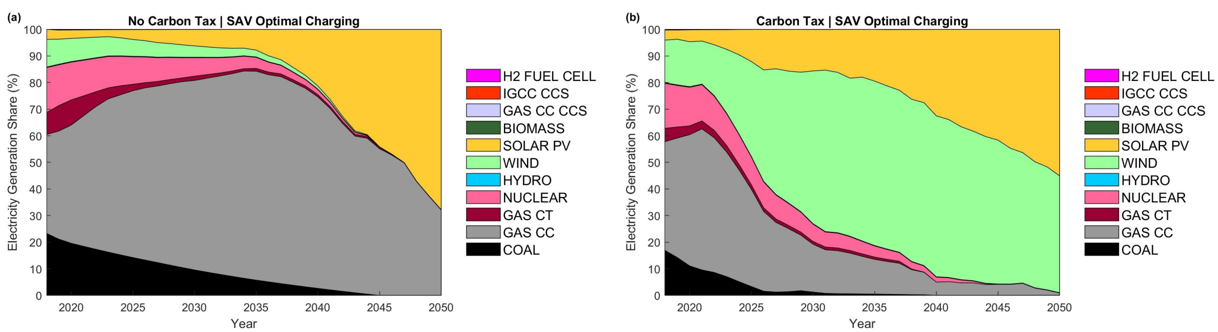

Figure 2.4. Evolution of the electricity generation mix without (a) and with (b) the carbon tax. The two scenarios plotted assume that shared VMT ultimately replace 70% of private VMT, that SAVs have no effect on travel demand, and that eSAV charging is optimally scheduled. Other than the policy setting, we find that these other scenario dimensions do not noticeably affect the generation mix.

The generation results in Figure 2.4 show that solar PV will expand in the long run regardless of the carbon policy context, due to large projected cost reductions. The most significant long-run effect of the carbon policy on the generation mix relates to the competition between wind and natural gas. Both technologies have properties that complement solar PV, since natural gas plants provide dispatchable peaking power, and wind in Texas has higher capacity factors at night when solar PV is unavailable. Without the carbon tax, natural gas generation continues to increase until 2035, when it accounts for 80% of electricity produced. From that point forward, solar PV expands rapidly. The 2050 generation mix consists of roughly 68% solar PV and 32% natural gas. Under the carbon tax, natural gas expands in the short run to a peak generation share of 56% in 2021, then declines thereafter. Wind electricity, which is completely eliminated in the absence of carbon policy, grows considerably in the presence of the tax. In addition to penalizing fossil fuel generation, the carbon tax induces a very high share of intermittent renewables, and in this context the temporal complementarity of solar PV and wind is valuable (i.e., solar PV is available during the day while wind capacity factors are highest at night). Under the tax, the 2050 generation mix is comprised of roughly 55% solar PV, 44% wind, and 1% natural gas.

Based on economics alone, solar PV accounts for a majority of the 2050 generation mix in all scenarios. As electricity production shifts toward solar PV, the value of optimally scheduling eSAV charging during the daytime to align with solar PV output increases. This synergy explains the faster and more complete market penetration of BEVs in the SAV fleet under optimal charging compared to night charging, previously observed in Figure 2.2. The optimal alignment of eSAV charging with solar PV output can be seen in Figure 2.5, which visualizes the hourly electricity dispatch computed by the model for the Summer season in 2050. The four depicted scenarios are the same ones that appeared in Figure 2.2, highlighting differences caused by varying assumptions about the carbon policy and eSAV charging paradigm. The pink areas below the horizontal axes represent the endogenous load associated with eSAV charging. If charging can be optimally coordinated, then it is primarily scheduled to align with the abundant solar power available during the daytime, visible as the yellow areas above the horizontal axes. Without a carbon policy, all optimal eSAV charging occurs during the daytime. Under the carbon tax, a small amount of optimal eSAV charging takes place at night. In this case, generation relies so heavily on intermittent renewables that SAV charging must compete with battery storage charging to absorb solar PV output during the daytime, so a tiny portion of eSAV charging is allocated to nighttime hours when the exogenous load is low relative to wind output. If eSAV charging must take place at night, then there is a limit to how many BEVs the SAV fleet can cost-effectively incorporate, and some HEVs are deployed to limit the stress on the electricity sector (see Figure 2.2).

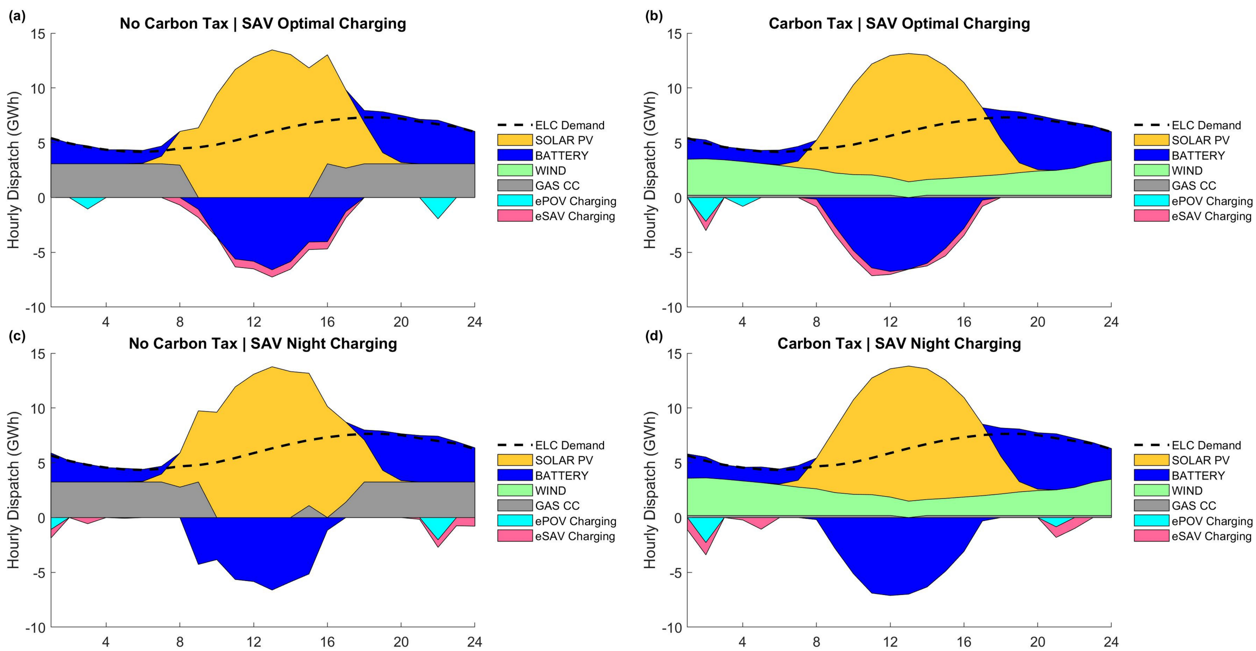

Figure 2.5. The optimal hourly electricity dispatch computed by the model for Summer 2050 in four scenarios distinguished by carbon policy and eSAV charging paradigm. All four scenarios assume that shared VMT ultimately replace 70% of private VMT, and that SAVs have no effect on travel demand.

As the electricity sector increasingly adopts intermittent wind and solar power, battery storage becomes an important component of the electricity system. Figure 2.6 illustrates the growth of battery capacity (in energy units) over time in all ten scenarios. By 2050, the POV Only scenarios (red lines in Figure 2.6) incorporate the greatest battery capacity. This result indicates that, by encouraging faster and more extensive adoption of electric transportation, SAVs add a flexible charging load to the system that reduces the need for battery storage. For the most part, the Optimal Charging scenarios (green lines) feature less battery storage capacity than their corresponding Night Charging scenarios (blue lines), due to the greater flexibility to synchronize eSAV charging and intermittent renewables output in the former.[4] The Carbon Tax scenarios (dotted lines) include more intermittent generation than their corresponding No Carbon Tax scenarios (solid lines), so battery storage expands more under the carbon tax. If SAVs induce double the VMT of the POVs they replace, then the eSAV charging demand increases and more battery storage is required.

2.5.3 Carbon emissions

Figure 2.7 shows the results for total annual CO_2 emissions in all ten scenarios. The most obvious grouping of the scenarios is by policy, with the No Carbon Tax (solid lines) and Carbon Tax (dashed lines) scenarios following dramatically different trajectories. Even in the No Carbon Tax scenarios, the declining costs of clean electricity and transportation technologies cause emissions to fall considerably beginning around 2035, and annual CO_2 emissions in 2050 are roughly half their 2015 level. The escalating carbon tax causes emissions to decline steeply after 2021, and reach near-zero levels by the 2050 time horizon.

Whether a carbon tax is present or not, the POV Only scenarios (red lines) without SAVs exhibit noticeably higher emissions than the other scenarios for most of the timeframe. In the No Carbon Tax case (solid lines), POV Only emissions peak later than emissions in any

[4]The last few model years under No Carbon Tax are an exception to this general observation. In this case, Night Charging causes HEVs to replace some BEVs in the SAV fleet (see Figure 2.2), leading to lower electricity demand than Optimal Charging and ultimately less battery storage capacity.

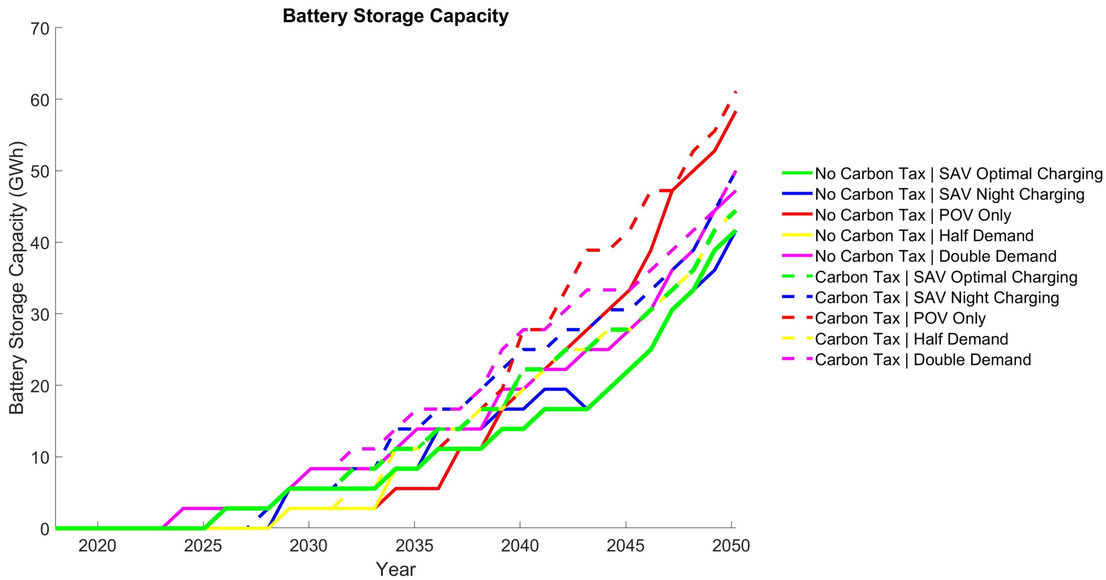

Figure 2.6. Growth of battery storage capacity (in energy units) over time in all ten scenarios.

scenario with SAVs, and at a higher quantity. The main result that emerges from Figure 2.7 is that, whether a carbon tax is present or not, SAVs reduce system-wide CO_2 emissions. Interestingly, this remains true even if SAVs induce double the VMT of the POVs they replace. Emissions do not appear to be sensitive to the SAV demand multiplier, especially under the carbon tax (dashed lines). The reason that emissions do not rise significantly with shared VMT is that the SAV fleet electrifies rapidly, and by the time SAV diffusion becomes widespread, the electricity used to charge them is mainly derived from renewables.

In the final years of the No Carbon Tax case, the scenario with SAVs and Night Charging (blue solid line) actually has higher emissions than the POV Only scenario (red solid line). As described in the earlier footnote, this outcome arises because less flexible night charging places enough stress on electricity generation to cause some HEVs to substitute for BEVs in the SAV fleet (see Figure 2.2). The Night Charging scenarios generally have the highest emissions of all scenarios with SAVs throughout most of the timeframe, even compared to the scenarios with Optimal Charging and Double Demand. To ensure that SAV adoption reduces CO_2 emissions, these findings suggest that optimally scheduling eSAV charging to align with renewable power output is an even more important step than constraining increases in travel demand.

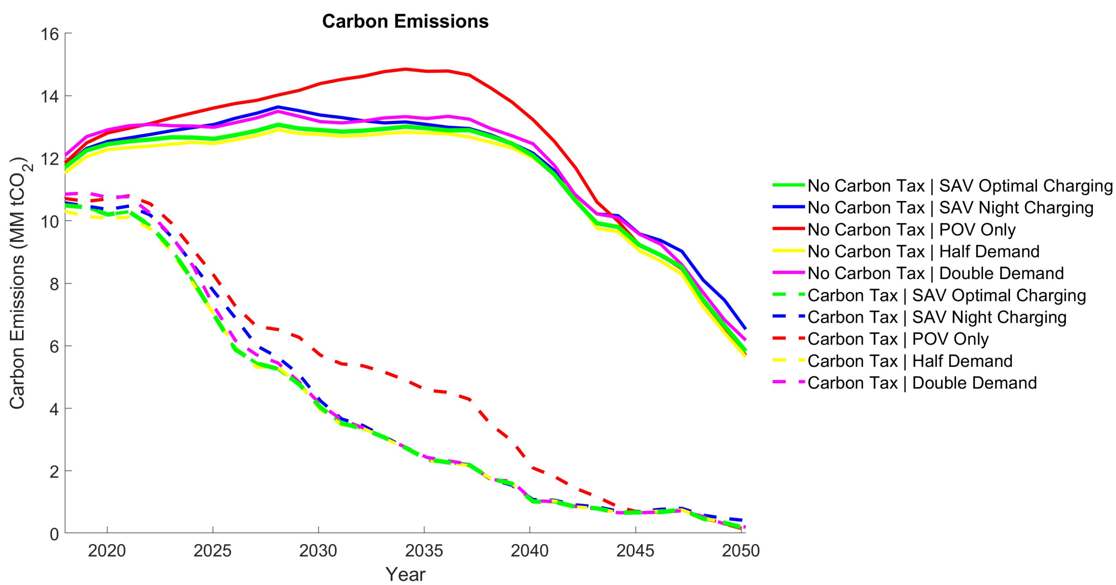

Figure 2.7. Total annual CO_2 emissions in all ten scenarios.

The differences in annual CO_2 emissions across the scenarios in Figure 2.7 can be attributed to numerous mechanisms, including differences in private VMT, shared VMT, electricity technologies, vehicle technologies, carbon policies, and eSAV charging paradigms. To elucidate the impacts of individual mechanisms on emissions, Figure 2.8 illustrates the evolving carbon intensity of transportation (in tCO_2 per thousand miles) in all ten scenarios. Emissions (numerator) and mileage (denominator) are both summed over private and shared vehicle travel.

In contrast to Figure 2.7 for total emissions, where the most obvious grouping is by carbon policy (solid vs. dashed lines), in Figure 2.8 for carbon intensity, the clearest grouping is by SAV scenario (different colors). Because the SAV fleet electrifies much faster than the POV fleet, the POV Only scenarios feature the highest carbon intensities for most of the timeframe. The difference between scenarios with and without SAVs is larger than the difference between the POV Only scenarios with and without the carbon tax. This striking result implies that encouraging the diffusion of SAVs can be an even more powerful lever than a carbon tax for reducing the carbon intensity of vehicle travel, especially in the short to medium term.

As expected, all Carbon Tax scenarios result in less carbon-intensive vehicle transportation than their corresponding No Carbon Tax scenarios. Eventually, near the end of the timeframe when the carbon tax reaches very high levels, emissions in the POV Only scenario with the carbon tax fall below those of the No Carbon Tax scenarios, and in 2050 the emissions profiles are primarily grouped by carbon policy.

The Night Charging scenarios (blue lines) tend to feature vehicle travel carbon intensities that fall between those of the POV Only scenarios and the scenarios with SAVs and Optimal Charging. Once again, this demonstrates the emissions reduction benefits that stem from the ability to optimally schedule electric vehicle charging, which would likely be easier to achieve with a centrally operated SAV fleet than with POVs. The demand multiplier associated with the substitution of SAVs for POVs has a noticeable, but not dominant, effect on carbon intensity. If SAVs induce additional VMT, this slows down the pace at which the carbon intensity of vehicle travel declines. With a sharper increase in shared VMT, there are more SAVs to electrify, and constraints on the rate of capacity expansion for each technology necessarily mean that electrification of a larger fleet will take longer. In addition, more eSAVs demand more electricity, so with a larger SAV fleet it might be necessary to schedule some charging during hours with more carbon-intensive electricity.

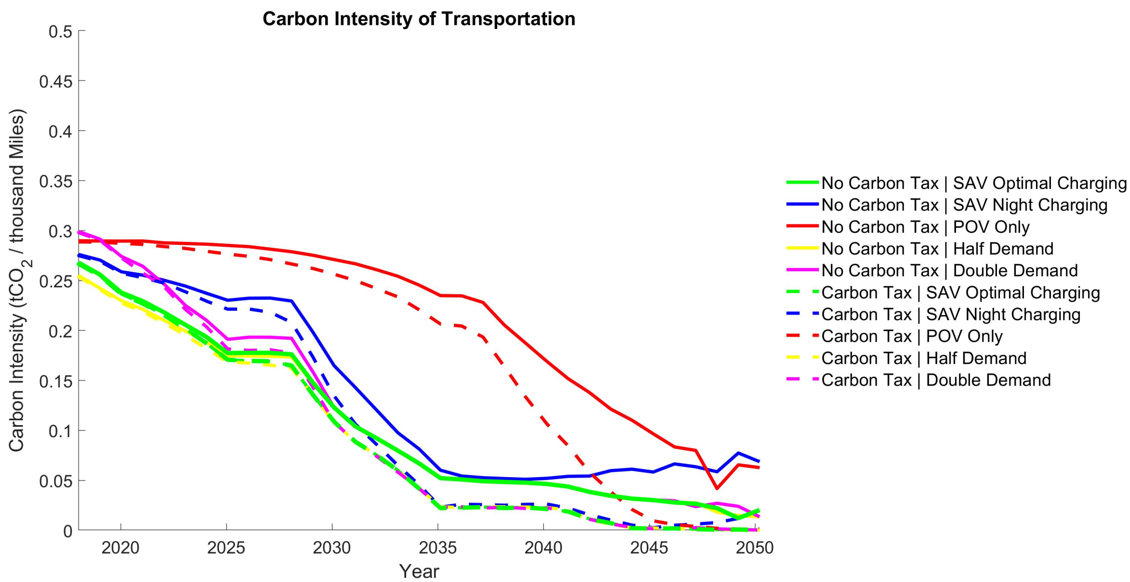

Figure 2.8. Carbon intensity of vehicle travel over time in all ten scenarios. The carbon intensity measures the vehicle CO_2 emissions per mile of vehicle travel, across both private and shared transportation.

Figure 2.9 shows how the carbon intensity of electricity (in tCO_2 per MWh) evolves over time in all ten scenarios. Unlike the carbon intensity of vehicle travel, the carbon intensity of electricity appears to depend only on the carbon policy. This is in line with our aforementioned finding that the carbon policy is the only scenario dimension which causes meaningful differences in the electricity generation mix. Therefore, the results cast doubt on the mechanism linking SAVs (and their faster electrification) to less carbon-intensive electricity generation by facilitating the integration of intermittent renewables into the power sector. In fact, the greatest benefit of SAVs that we observe in the electricity system is their ability to reduce the required battery storage capacity (see Figure 2.6).

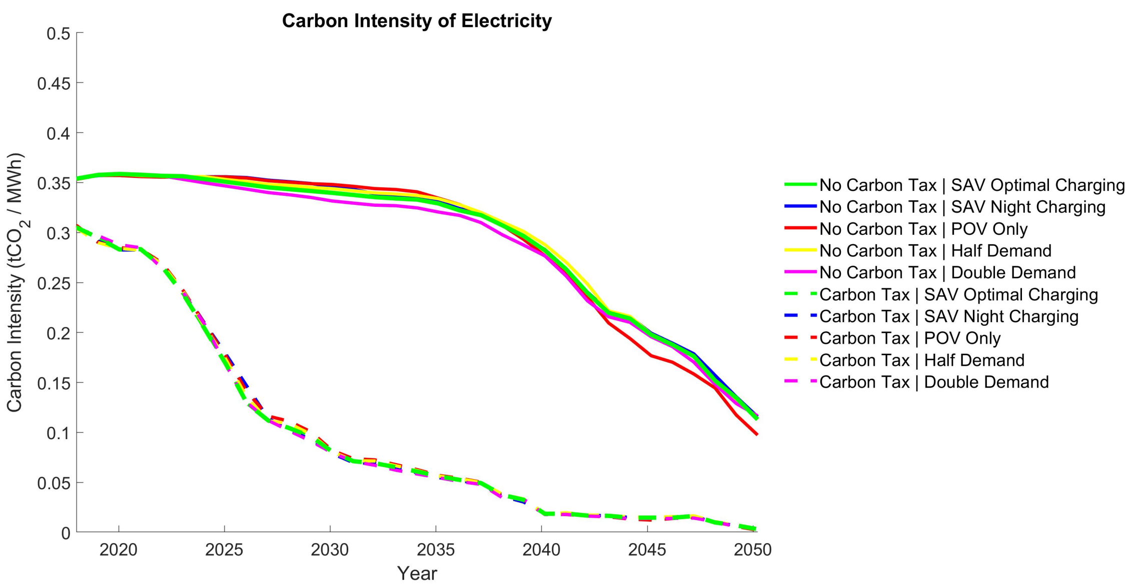

Figure 2.9. Carbon intensity of electricity over time in all ten scenarios. The carbon intensity measures the electricity sector CO_2 emissions per MWh of electricity generated.

2.5.4 Net present costs

The net present costs of satisfying all electricity and transportation demands over the complete model timeframe are depicted in Figure 2.10 for all ten scenarios. The height of each bar is equivalent to the minimized objective value of the optimization problem in each scenario. As expected, the net present costs in the Carbon Tax scenarios are higher than the net present costs in their corresponding No Carbon Tax scenarios. For a given set of assumptions about SAVs, the difference between the Carbon Tax and No Carbon Tax objective values represents the cost of the carbon policy.

The widespread diffusion of SAVs reduces costs significantly compared to the POV Only scenarios. The results in Figure 2.10 show that the cost savings associated with the transition to SAV transportation more than offset the additional cost imposed by the Carbon Tax.

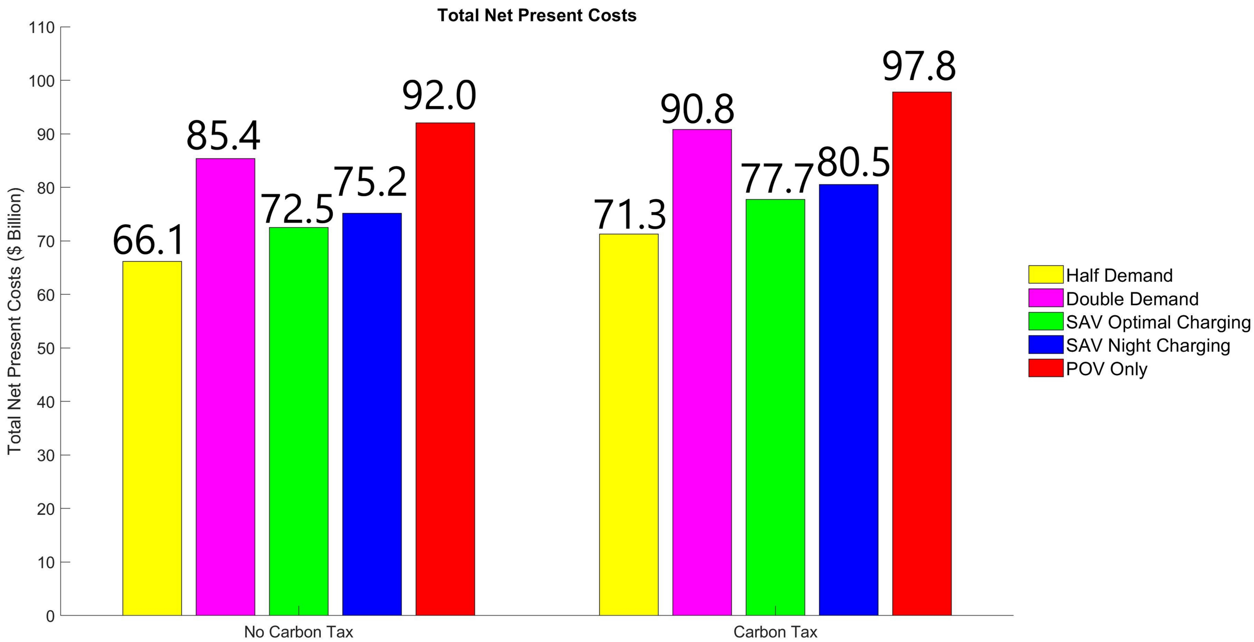

Figure 2.10. Net present cost of satisfying all electricity and transportation demands over the complete model timeframe in each scenario. The height of each bar is equivalent to the minimized objective value of the optimization problem.

In other words, the red bar in the No Carbon Tax group on the left in Figure 2.10 is higher than all of the non-red bars in the Carbon Tax group on the right. Interestingly, the combination of the Carbon Tax and SAV diffusion still results in net cost savings even if each SAV induces double the VMT of the POV it replaces. Uptake of SAVs reduces costs primarily by satisfying transportation demand using a much smaller number of vehicles that operate with much higher utilization factors than POVs. The reduction in fleet size has a much larger effect than the incremental cost premium of each SAV technology relative to its corresponding POV version, which works in the opposite direction. The ability to drastically reduce capital investments by achieving higher utilization of capital assets is a core motivation for the sharing economy, and it is borne out in our scenario results for net present cost. Other minor channels through which SAVs reduce costs include some of the distinctions outlined in Table 2.1, such as their assumed 10% fuel efficiency advantage and the fact that they can be economically dispatched.

The value of Optimal Charging relative to Night Charging for eSAVs in each policy setting appears as the vertical difference between the green and blue bars in Figure 2.10. The economic value of being able to align eSAV charging and renewable power output is substantial. Optimal Charging reduces net present cost by 3.6% under No Carbon Tax and 3.5% under the Carbon Tax. Cost saving mechanisms include charging eSAVs during hours with low-cost electricity, and reducing charging peaks that would necessitate greater investments in generation and/or battery storage capacity. Recalling our earlier finding that Optimal Charging leads to significant reductions in CO_2 emissions, intelligently scheduled charging has the potential to yield major economic and environmental benefits simultaneously.

2.6 Conclusions

In this study, we expand the OSeMOSYS energy system optimization model to explore the potential contributions of SAVs to climate change mitigation efforts. This modeling framework represents the integrated electricity and transport sectors and captures a rich set of mechanisms through which SAVs could influence CO_2 emissions and transportation costs. The database we construct applies OSeMOSYS to Austin, Texas, which is a valuable test setting due to its ambitious climate policy, currently heavy reliance on personal automobiles for transportation, and previous studies in the literature that assessed SAV fleet operations and climate policy in Austin (Brozynski and Leibowicz, 2018; Chen et al., 2016; Fagnant and Kockelman, 2014, 2018). By comparing the results of ten "what-if" scenarios differentiated by assumptions about SAV diffusion, carbon policy, the ability to optimally schedule eSAV charging, and the effect of SAVs on travel demand, we identify several important considerations for ensuring that a transition to SAV travel yields economic and environmental benefits.

We find that the diffusion of SAVs produces major economic and environmental benefits, and that the magnitudes of these benefits are sensitive to assumptions about SAV transportation. The SAV fleet is a favorable market segment for HEVs, PHEVs, and BEVs, due to high utilization rates that make vehicles with higher capital costs but lower variable costs more attractive. Even in the absence of carbon policy, the SAV fleets in our scenarios electrify quickly and extensively. This electrification trend is a powerful CO_2 emissions reduction lever given that electricity generation decarbonizes considerably in the No Carbon Tax cases, and almost completely in the Carbon Tax cases. Judged by their effects on the carbon intensity of vehicle travel (CO_2 per mile), the diffusion of SAVs and associated electrification decarbonize the transport sector faster than the modeled carbon tax. The transition to SAVs also yields large cost savings, primarily by satisfying vehicle travel demand using a much smaller number of vehicles that requires far less capital investment. The ability to drastically reduce capital expenditures by making fuller utilization of capital assets is a core motivation for the sharing economy. This conclusion has been reached in numerous other recent studies, notably the report by Fulton et al. (2017) that found larger benefits from deploying autonomous vehicles as shared rather than personally owned vehicles.

Somewhat strikingly, we consistently find that the ability to optimally schedule eSAV charging is a more important determinant of positive environmental and economic outcomes than the travel demand effect of SAV adoption. The SAV fleet can be expected to electrify fairly rapidly and extensively, and by the time SAVs become widespread, the electricity generation mix is projected to be far less carbon-intensive than it is today. The ability to optimally align eSAV charging with renewable generation is particularly important as the generation mix shifts toward solar PV. Optimized charging schedules ensure that eSAVs are charged using low-cost, carbon-free power while helping the system avoid additional investments in generation capacity or battery storage capacity. Therefore, incentivizing fleet operators to charge eSAVs at times that are optimal for the energy system as a whole appears to be a more important environmental policy priority than constraining a potential increase in travel demand. Even if SAVs induce double the VMT of the POVs they replace, they would still make the energy system cheaper and greener than one featuring only POVs. Optimally coordinated charging further enhances their environmental and economic benefits.

Therefore, if you are thinking about the implications of SAVs, emphasizing charging in alignment with renewables or other carbon free power is more important from a GHG perspective then even significant induced changes in VMT. Policies that incentive customers to charge at those times using things like time varying prices to ensure fleet operators face dynamic prices are recommended. This also applies to POVs, if policy makers can find ways to incentivize owners to charge their EVs during peak power production they can significantly lower GHG and electricity costs. Policy makers looking to reduce GHGs and lower electricity costs should look favorably at SAV development because they are more likely to be amenable to optimal charging with minimal public investment. Furthermore, if significant numbers of POVs become electric policies and investments that incentivize owners to charge during the day, such as expanded charging infrastructure at places of work and daytime business, will also reduce GHGs and lower electricity costs.

As always, our findings should be interpreted in light of the limitations of the modeling framework. Our top-down, integrated modeling perspective abstracts away from many nuances of vehicle operations and transportation networks, which are not the focus of our study. We do not account for the costs of charging and refueling infrastructures, which vary by vehicle technology and are likely different for POV and SAV variants. Our scenario design creates some stark dichotomies that are simplifications of reality, such as the idea that all eSAV charging could be optimized while all ePOV charging could not be, or the fact that ridesharing and automation are only available in their combined form as SAVs. For example, Bösch et al. (2018) suggest that shared vehicles might not be the most efficient autonomous option, and private owners would accept the higher costs of autonomous vehicles. Furthermore, other studies such as Fulton et al. (2017) model automation and ridesharing separately, and imply that their combination is not a foregone conclusion. Our scenarios assume an exogenous division between separate private and shared VMT demands rather than allow these two modes to compete with one another for market share. The latter approach could be implemented using a discrete choice formulation for mode selection and technology adoption. However, our "what-if" scenario analysis has been useful for generating insights about the relative magnitudes of various mechanisms through which SAVs could influence GHG emissions. We have provided evidence to suggest that SAV diffusion will yield economic and environmental benefits, and contribute to cost-effective climate change mitigation.

Acknowledgments

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Chapter 3

Co-optimization and community: Maximizing the benefits of distributed electricity and water technologies

3.1 Introduction

[1] Distributed water technologies (DWTs) and distributed energy technologies (DETs) can provide a wide range of benefits. They reduce a household's reliance on centralized infrastructures, which can improve resilience in disaster situations and make the home's access to water and electricity less vulnerable to cascading failures across water and electricity networks (Falco and Webb, 2015; Wang et al., 2016). Depending on the distributed technologies adopted, their patterns of operation, and their geographical and infrastructural context, they can reduce a household's water and electricity bills and lower its carbon footprint (Deetjen et al., 2018; O'Shaughnessy et al., 2018; Valdez et al., 2016; Vitter et al., 2018). Distributed technologies also have the potential to democratize decision making over natural resources by giving individuals greater autonomy over their water and energy choices (Koch and Christ, 2018; Koirala et al., 2016). From the higher-level perspective of water and electricity system planning, distributed technologies can reduce the strain that population and economic growth put on centralized infrastructures. They can help reduce the need for

[1]This work has been previously published where I contributed to the design of the model, interpreted the results, created the graphics, and wrote the text of the paper. Citation: Jones, Erick C., and Benjamin D. Leibowicz. 2021. "Co-Optimization and Community: Maximizing the Benefits of Distributed Electricity and Water Technologies." Sustainable Cities and Society.

expensive expansions of existing networks (Vitter et al., 2018) and cost-effectively improve access to electricity and clean water in developing regions (Levin and Thomas, 2016).

However, despite their myriad benefits, few households or communities invest in distributed technologies and those that do are typically more affluent (Koch and Christ, 2018). Some experts point to land requirements, long payback periods, and intermittency as key factors that discourage adoption (Koch and Christ, 2018; Levin and Thomas, 2016; O'Shaughnessy et al., 2018). Other experts believe that utility-scale investments and the economies of scale they provide will in most cases be cheaper than any distributed technology (Eggimann et al., 2015, 2016; Levin and Thomas, 2016). Still, some analysts contend that the market and distribution structure of the existing electricity system hinders meaningful adoption more than any other factor (Dyson et al., 2018; Hirsch et al., 2018; Leigh and Lee, 2019; The Johnson Foundation at Wingspread, 2014).

In this study, we investigate the conditions that promote adoption of distributed technologies, focusing on the benefits of co-optimizing distributed water and electricity systems, and of investing at the community scale (rather than home scale). First, we explore when distributed electricity and water technologies are economical alternatives to centrally supplied electricity and water at current costs. Then, we investigate how different levels of aggregation affect the cost-effective adoption of distributed systems. Finally, we analyze whether co-optimizing investments in – and operation of – distributed electricity and water technologies improves their combined economics, stimulates additional adoption, and reduces greenhouse gas (GHG) emissions.

To explore these ideas, we develop a mixed-integer linear program that optimizes distributed technology capacities and hourly dispatch. We test our model through a case study of a neighborhood in Austin, Texas that leverages household-level empirical data on rooftop solar outputs and water and electricity demand profiles. Previous studies have examined water and electricity independently using real-world demand profiles (Blinco et al., 2017; Bradshaw and Luthy, 2017) or in conjunction using hypothetical input data (Awal et al., 2019; Elasaad et al., 2015; Fan et al., 2019; Valdez et al., 2016; Ward et al., 2012). Other studies have compared distributed versus utility-scale generation (Eggimann et al., 2015, 2016; Latreche et al., 2018) or household versus community generation (Hledik et al., 2018; Vitter et al., 2018). Our study adds to the literature by being the first to incorporate all these elements within a unified optimization model: co-optimization of distributed water and electricity investments and operations; choices among household, community, and centralized systems; and empirical household-level time series data.

To preview our findings, our results show that distributed technologies are still relatively expensive, but they can compete economically with utility-supplied electricity and water in certain contexts, especially if they are invested in at the community scale and are co-optimized. Community-scale aggregation can significantly enhance the prospects for distributed electricity and water by taking advantage of economies of scale, spreading out fixed costs over more households, and aggregating heterogeneous demand profiles. A co-optimized distributed energy and water system (DEWS) can achieve synergies that make it more attractive than the sum of its parts by flexibly operating DWTs to consume surplus distributed electricity at times of abundance.

The remainder of this article is structured as follows. Section 2 reviews the most relevant literature on DETs and DWTs, community-scale applications, modeling of distributed energy and water systems, and co-optimization. Section 3 describes our methodology including the model and case study data. We outline the scenarios that we run and compare in Section 4. Section 5 presents and discusses the scenario results. We conclude in Section 6 with a summary of our most important findings, acknowledgment of limitations, and directions for future research.

3.2 Literature review

3.2.1 Background on distributed energy and water technologies

This subsection provides background information on some prominent DETs and DWTs, including their functions, real-world applications, and benefits. This brief review cannot possibly span the full breadth of DETs and DWTs that may play important roles in the future. Therefore, we focus on those DETs and DWTs which are strong candidates for widespread adoption in the near future, and which we incorporate into our model for this paper. Further technical details of these technologies, including our parameter assumptions for performance and cost, are found in Section 4.3.6.

3.2.1.1 Distributed energy technologies

DETs, which are also commonly referred to in the literature as distributed energy resources (DERs), generate and/or store electricity, are installed and operated independently from the utility, and can interact with the local distribution system (Latreche et al., 2018; Lawrence and Vrins, 2018). The Electric Reliability Council of Texas (ERCOT) defines a DET as a generation and/or storage technology that is interconnected at or below 60kV and operates in parallel with distribution. DETs include solar photovoltaics (PV) which convert light into electricity, (smaller) wind turbines which capture wind energy using large blades and convert it into electricity using a mechanical turbine, batteries which store energy to be discharged at a later time, small-scale combined heat and power systems, and other similar technologies (Akorede et al., 2010; The Brattle Group and Electric Reliability Council of Texas, 2019). While utility-scale "macrogrids" produce gigawatts and transmit electricity hundreds or thousands of miles, microgrids are made of groups of DETs that have more limited capacities (Hirsch et al., 2018). Nonetheless, the ability of DETs to decentralize, decarbonize, and democratize electricity systems from the bottom-up rather than top-down as the current utility-scale system does has made them a subject of vast interest to researchers and policymakers alike (Carvallo et al., 2020; Green, 2016).

DET adoption remains low relative to the scale of the full electricity system, but is increasing (Hirsch et al., 2018). DETs can enhance grid reliability (Xu et al., 2017), and a system optimized for DETs can reduce the complexity of the current grid and improve cost and quality (Kristov et al., 2016). Because of these and other factors, ERCOT now has 1300 MW of distributed generation (62% growth in only two years), mostly solar but with some small-scale distributed wind (The Brattle Group and Electric Reliability Council of Texas, 2019). Nonetheless, due to a lack of know-how, regulatory barriers, and capital constraints facing potential adopters, DETs are far from full market penetration (Dyson et al., 2018).

Projects beyond typical solar and wind installations are also becoming more prevalent. Hybrid solar, wind, and storage facilities are appearing all over the world. The Skeleton Creek Project which will integrate 250 MW each of solar and wind with 200 MW of battery capacity will be completed in Oklahoma by 2021 (Eller, 2019). Community solar projects are also expanding; for example, a project in Houston repurposed a 240-acre landfill to host 70 MW of solar panels owned by the community (Wolfe Energy LLC, 2019).

3.2.1.2 Distributed water technologies

Water infrastructure, like energy infrastructure, is often dated both physically and conceptually. Water sources are becoming increasingly scarce and repairs to the existing infrastructure are becoming increasingly expensive. New solutions, especially local solutions, are needed (Leigh and Lee, 2019; The Johnson Foundation et al., 2012; The Johnson Foundation at Wingspread, 2014).

DWTs capture and/or recycle water near the point of use rather than at a centralized facility. These technologies include rainwater harvesting, stormwater capture, graywater recycling, and small water recycling facilities (WRFs). Rainwater harvesting captures rainwater and stores it in a tank to be later pumped and sometimes filtered back to an end user. Stormwater capture works like rainwater harvesting except it captures stormwater runoff, usually from roads and other paved surfaces. Graywater recycling captures used water (graywater) from most residential sources, except for toilets which produce blackwater. WRFs capture water on site and treat it to drinking standards using technologies like reverse osmosis or UV filtration (Makropoulos et al., 2010; National Academies of Sciences Engineering and Medicine, 2016; National Research Council, 2012). In contrast, traditional water systems withdraw water from basins like rivers or lakes, purify that water, pump it to each end user, and then collect the wastewater from each point of use for return back to a centralized plant for treatment (National Research Council, 2012). The traditional system requires massive infrastructure investments (National Research Council, 2012) and has high embedded energy (Awal et al., 2019); DWTs generally do not.

The ability of DWTs to make up for limited or poor-quality water supplies has encouraged rainwater harvesting in Texas, especially in rural areas (Barer, 2012). Stormwater capture requires coordination with more people or organizations but can provide quantities of water much larger than rainwater harvesting, so it is used in municipalities with constrained water supplies like Los Angeles (National Academies of Sciences Engineering and Medicine, 2016). Furthermore, water supplies can be augmented through water recycling technologies like graywater reuse or WRFs. This is popular in countries with minimal fresh water sources, like Singapore, which receives 40% of its water from reuse (National Research Council, 2012; Vitter et al., 2018).

DWTs are drawing much interest as a solution to water infrastructure problems due to their potential to improve sustainability and resilience via recycling and resource conservation (Leigh and Lee, 2019), lower capital and operating costs (Ajami et al., 2018), and ability to complement and not just replace the centralized system as a hybrid system (Sapkota et al., 2015). DWTs have important features in common with DETs, and some studies have looked at how similar market mechanisms could be applied (Ajami et al., 2018). Nonetheless, despite their benefits, DWT adoption in the U.S. remains limited (Leigh and Lee, 2019; National Research Council, 2012). DWTs face significant barriers to large-scale adoption because of socio-institutional impediments and lock-in effects (Leigh and Lee, 2019), as well as safety concerns (The Johnson Foundation at Wingspread, 2014).

3.2.2 Community-scale distributed energy and water applications

Many studies investigate how home-scale DETs and DWTs compare to centralized utilities, but there are compelling reasons to believe that the community scale is a promising aggregation level for investing in distributed technologies (Leigh and Lee, 2019). For example, Hledik et al. (2018) show how net zero initiatives that focus solely on the household level omit an appealing option in the form of community solar, which enables significant savings compared to investments for individual homes. Chwastyk et al. (2018) study different community solar design models to calculate cost saving potentials and assess market penetration rates.

While centralized solutions benefit from economies of scale and high efficiencies (especially when co-optimization takes place at the utility scale, e.g., combined heat and power plants fueled by biogas from wastewater treatment facilities (EPA, 2007; Gu et al., 2017)), they can also suffer from diseconomies of scale when they have to serve a vast number of end users. On the other hand, community-scale systems can flexibly match growing demand with "just-in-time" investments and avoid costs of idle capacity in both production and distribution networks (Wang, 2014). Furthermore, community-scale solutions, like community solar, expand access to those who could not afford single-home investments, reduce the upfront cost any one person has to pay, and lower the hassle of installation and maintenance (Coughlin et al., 2010; Hoffman and High-pippert, 2015).

This study evaluates the extent to which community-scale distributed resource deployment results in more favorable economics than home-scale distributed systems.

Even as home-scale solutions become more affordable, community-scale solutions still offer numerous advantages. By comparing different levels of aggregation, we aim to contribute new insights on the synergies between energy and water systems at various scales.

3.2.3 Distributed energy and water modeling

3.2.3.1 Distributed energy modeling

Many studies model how DETs interact with the centralized electricity system, though their methodologies and levels of granularity vary. For instance, Levin and Thomas (2016) create a general decision support framework to compare extending the grid to investing in distributed solar. Latreche et al. (2018) develop multiple formulations to determine the optimal level of distributed generation integration as a single- or multi-objective optimization problem, and experiment with several different solution strategies. O'Shaughnessy et al. (2018) evaluate an integrated approach to solar deployment called "solar plus" that combines solar, energy storage, and load control into one system. They use a techno-economic time series model from the National Renewable Energy Laboratory (NREL) called the Renewable Energy Optimization model (RE-Opt) and parameterize it with inputs based on another NREL tool (PVWatts). They find that the solar plus approach improves user economics across a wide variety of rate structures. Deetjen et al. (2018) create a mixed-integer linear program to model the optimal equipment capacity and dispatch of a central utility plant using hourly data from 123 homes. The authors demonstrate that the central utility plant provides economic benefits to the neighborhood even though it does not incorporate much rooftop solar and could worsen net demand ramp rates faced by the utility. Carvallo et al. (2020) develop a sequential optimization procedure to model decentralized decision making on distributed solar and battery storage investments. Customers make their own DET investment choices, and then the utility must plan its resources accordingly. Their results show that better coordination between distributed and utility-scale electric investments could yield very large cost savings.

3.2.3.2 Distributed water modeling

The modeling literature on water recycling and wastewater treatment systems is vast and comprises different scales, areas, uses, and treatment technologies (Barker et al., 2016; DeOreo et al., 2016; Guo et al., 2014; Makropoulos et al., 2010; National Academies of Sciences Engineering and Medicine, 2016; Yu et al., 2015). Examples include studies which analyze how recycled water can address drought in California (Cohen, 2009), reduce the amount of economically recoverable water that is wasted in Texas (Loftus et al., 2018), or provide another economical source of water (Brown and Recycling, 2007; Morelli and Cashman, 2019).

Other previous research explores how distributed water systems would operate in more detail. Falco and Webb (2015) outline how electricity microgrid concepts can provide a framework for water microgrids. Roefs et al. (2017) evaluate the economic performance of centralized wastewater treatment, a community water treatment facility, and a hybrid approach under different urban growth scenarios using Monte Carlo simulations for urban growth, infrastructure design properties, and discounted asset lifetime costs. Eggimann et al. (2015, 2016) develop heuristic algorithms to determine the optimal level of aggregation for water infrastructure. Vitter et al. (2018) compare the financial cost of a community-scale WRF to centralized water treatment service using a mixed-integer linear program with batch processes for treatment.

3.2.4 Integrated energy-water models

The research literature on the water-energy nexus is expanding as energy and water resources become scarcer and their interrelatedness is increasingly viewed as an asset rather than a liability. Some studies examine narrow cases of the water-energy nexus. For example, Ward et al. (2012) benchmark the energy consumption of rainwater harvesting systems. Fan et al. (2019) use an urban metabolism framework to investigate how the water-energy nexus could be leveraged to conserve resources in a city. Other analyses construct specific case studies to show how solar energy can be used for water purification via desalination (Shatat et al., 2013) or reverse osmosis membranes in undeveloped Mexico (Elasaad et al., 2015).

Awal et al. (2019) use a simulation model to determine irrigation requirements for turf grass in Houston, calculate the corresponding energy inputs needed to clean the irrigated water sourced from the municipal water supply, and investigate how different irrigation techniques could reduce water and energy demands. While their study examines the water-energy nexus, it considers only one end-use demand (irrigation water) and employs a simulation approach that cannot automatically generate optimal decisions. Valdez et al. (2016) design a simulation model to compare the water consumption, energy consumption, and carbon emissions of buildings in Mexico City when fully supplied by utilities versus incorporating different rainwater harvesting systems. This model simulates rainwater harvesting strategies instead of allowing an optimization model to choose investments and dispatch. Furthermore, while Valdez et al. (2016) compute water and energy outcomes, the model's distributed investments are limited to DWTs. Gold and Webber (2015) develop a water treatment model, an energetic model, and an integrated optimization scheme to explore how desalination, solar, and wind technologies could operate in tandem. The optimization scheme uses information gathered from the other two models to determine an operational schedule to desalinate water using solar and wind energy.

At far more macro scales in terms of space and time, integrated assessment models (IAMs) of coupled energy, economic, and environmental systems have evolved to capture water-energy nexus interactions in more detail (Wilkerson et al., 2015). For instance, the Global Change Assessment Model has been applied to assess the long-run balance between water supply and demand at the basin scale, considering water use for energy (e.g., power plant cooling, hydroelectricity, bioenergy crops) and climate change (Kim et al., 2016). However, the spatial and temporal resolutions of IAMs tend to be too coarse to capture the differences between utility-scale, community-scale, and distributed-scale technology deployment.

In some respects, our work is a natural extension of Vitter et al. (2018) in that we formulate a mixed-integer linear program to optimize DWT investments and operations, but we add the ability to invest in DETs as an alternative to grid electricity for powering DWTs and satisfying all other electricity demand. Our model also considers a larger menu of technologies, whereas Vitter et al. (2018) primarily focus on a reverse-osmosis-based WRF. It should also be noted that our model is similar in spirit to other optimization frameworks that couple representations of electricity supply options with end-use technologies in other sectors that require electricity. For instance, Brozynski and Leibowicz (2018) and Jones and Leibowicz (2019) follow similar approaches to co-optimize electricity and transportation investments, where electric vehicle charging can be scheduled to maximize utilization of solar and wind resources.

3.3 Methodology

3.3.1 Model overview

We develop a DEWS optimization framework structured as a deterministic mixed-integer linear program (MILP) that minimizes the annual net cost of satisfying the water and electricity demands of a household or group of households. The optimization scheme endogenously chooses which technologies to install, how much capacity to invest in, and the operational level for each hour of the year. The system must operate according to a host of resource and engineering constraints.

We formulate our model as an MILP to capture the "lumpy" nature of investments at the home and community scales. Certain DWTs and DETs are available only in discrete sizes, so integer variables are a more appropriate choice than continuous variables for representing their investment decisions. Furthermore, the MILP structure allows us to incorporate economies of scale that reduce investment costs in per-unit terms as DWT and DET capacities are added in larger increments. This is an important factor for comparing single-home and community levels of aggregation, and the MILP formulation is a computationally easier way to capture economies of scale than a nonlinear optimization model.

To tailor the model to a particular application, the input database requires information on technology costs, technology performance, utility water and energy rates, water and energy demands, and water and energy resources (e.g., rainfall, solar availability). It is built to enable tiered utility rate structures which are often encountered in practice, where the marginal cost rises as threshold consumption levels are exceeded. The model is designed to span a timeframe of one year, with all investment costs annualized so that they can be fairly compared to operating costs. Dispatch is computed at an hourly resolution for a total of 8760 operational timeslices. This highly granular temporal resolution is necessary to accurately represent intermittent resources, capture time-varying demands, and model water and energy storage technology operations.

3.3.2 Key model equations

This subsection provides and explains some of the key equations in our model. These include the objective function, the supply-demand balance constraints, and special constraints designed to implement tiered rates, operate a community-scale DEWS, and govern storage technology operations.

The objective function for cost minimization is specified in Eq. (3.1). The first line includes the investment costs for DWTs and DETs, which consist of two terms. The first is the product of the installed capacity (continuous) and a per-unit capital cost, while the second is the product of the purchase decision (binary) and a fixed cost that does not scale with the amount of capacity added (i.e., it is the same for any positive addition). The second line includes operating costs incurred through dispatch. Water and electricity purchases from the utility in each tier of the rate structure are represented as "technologies," such that the rates themselves are featured as variable costs. The t, l, and m indices refer to technologies, timeslices, and months, respectively. The endogenous variables are in bold to distinguish them from the exogenous parameters.

$$\begin{aligned}
&\text{minimize} \quad \sum_t (CapitalCost_t * \boldsymbol{InstalledCapacity_t} + FixedCost_t * \boldsymbol{Purchase_t}) \\
&+ \sum_{t,l,m} \boldsymbol{ProducedTech_{t,l,m}} * VariableCost_t
\end{aligned} \tag{3.1}$$

Balance equations for each hour ensure that all demands are satisfied. The three demands are electricity, whitewater, and total water. Demand for electricity consists of both an exogenous component, representing the existing load profile of the household, and an endogenous component, which reflects the electricity requirements of installed DWTs based on their optimized dispatch schedule. Given the presence of water and energy storage technologies, resources sent into storage appear as endogenous demands that must be met in that hour, and resources released from storage contribute to supply in that hour. Electricity and water resources that are not used or stored in the hour they are produced are curtailed. Note that curtailment could be a normal feature of the optimal solution, especially for renewable electricity that has zero marginal cost (e.g., solar PV) but is fairly expensive to store for later use. However, the cost minimization objective combined with the ability to purchase utility water and electricity will generally steer the model away from investing in distributed technologies whose production would largely be curtailed. The total water constraint ensures sufficient supply of whitewater and graywater in aggregate, whereas the additional whitewater constraint recognizes that graywater can only be used for certain residential uses (e.g., irrigation, toilet flushing). Eqs. (3.2), (3.3), and (3.4) are the balance constraints for electricity, total water, and whitewater, respectively.

$$\sum_{t \in ELC} \boldsymbol{ProducedTech_{t,l,m}} = SpecifiedDemand_{kWh,l,m} * MonthlyDemand_{kWh,m} + \sum_{t \in ELC} (\boldsymbol{StorageAdded_{t,l,m}} + \boldsymbol{Curtailment_{t,l,m}} + \boldsymbol{ConsumedEnergy_{t,l,m}}) \quad l = 1, ..., 744, m = 1, ..., 12 \tag{3.2}$$

$$\sum_{t \in W} \boldsymbol{ProducedTech_{WW,l,m}} + \boldsymbol{ProducedTech_{GW,l,m}} = SpecifiedDemand_{gal,l,m} * MonthlyDemand_{gal,m} + \sum_{t \in W} (\boldsymbol{StorageAdded_{t,l,m}} + \boldsymbol{Curtailment_{t,l,m}}) \quad l = 1, ..., 744, m = 1, ..., 12 \tag{3.3}$$

$$\sum_{t \in WW} \boldsymbol{ProducedTech_{t,l,m}} \geq SpecifiedDemand_{Water,l,m} * MonthlyDemand_{WW,m} + \sum_{t \in WW} (\boldsymbol{StorageAdded_{t,l,m}}) \quad l = 1, ..., 744, m = 1, ..., 12 \tag{3.4}$$

3.3.3 Tiered rates and community-scale operations

Our model features several novel constraints added to implement tiered rate structures for utility electricity and water, and to ensure that these tiers continue to function properly in scenarios solved at the community scale. Eq. (3.5) represents the balance equations for all houses in the community. The f and h indices refer to the resource demanded (water, whitewater, or electricity) and home, respectively.

$$\sum_{t} (\boldsymbol{HouseTech_{f,t,h,m}} + \boldsymbol{HouseUtility_{f,t,h,m}}) \geq HouseDemand_{f,h,m} \quad \forall f, h, m \tag{3.5}$$

Even when the DEWS is optimized at the community scale, tiered rates must still apply to each individual home's purchases of utility resources. Eq. (3.6) imposes an upper bound on the amount of the utility resource that can be purchased within each tier, and also prohibits households from transferring the resource among each other to avoid paying the higher marginal costs associated with higher tiers. Mathematically, the constraint requires that a binary variable, which decides whether a house enters a specific utility tier, multiplied by the upper bound of that tier, is greater than what the house receives from that tier in a given month. If the house chooses not to enter that utility tier, then the binary variable is zero, and if it does decide to enter the tier, then it can only purchase up to the upper bound of the tier. Note that we do not need constraints to mandate that the home purchase from the tiers in ascending order of marginal cost, as this will automatically be the case due to the cost minimization objective.

$$\begin{aligned} &\boldsymbol{HousePurchase_{f,t,h}} * UpperBound_t \geq \sum_m \boldsymbol{HouseUtility_{f,t,h,m}} \\ &t \in Utility, \forall f, h \end{aligned} \tag{3.6}$$

3.3.4 Case study and input data

As a case study, we apply our model to a sample of real-world homes in Austin, Texas equipped with rooftop solar PV. Pecan Street Inc. Dataport (2016) provides a dataset with home-level electricity and water demand profiles, weather data, and some rooftop solar generation data for the full year 2016. We obtain data on technology performance and cost parameters from other sources to fully instantiate the model with input data for the case study.

City of Austin (2019) and Austin Water (2019a) employ rate structures with five tiers, where the marginal per-unit costs of electricity and water utilities increase as a household consumes more in a given month and moves into higher price tiers. These tiered rates are implemented using the constraints in the preceding subsection.

3.3.5 Distributed technologies

The case study database includes menus of DETs and DWTs that the model can invest in. All of these technologies have been deployed in real-world applications, and corresponding technical and cost data are available. However, technical and cost assumptions are subject to uncertainty, especially for the technologies with only a few existing installations.

The DETs available in our case study application are:

- Household rooftop photovoltaic panels (RFT-PV) (0-15 KW unit capacity)
- Community-scale photovoltaic panels (COM-PV) (100-250 kW unit capacity)
- Wind turbines (WIND) (250-1000 kW unit capacity)
- Wind and solar hybrid system (HBRD) (2.5 MW unit capacity)

The DWTs available in our case study application are:

- Household rainwater harvesting (RWH) (0-5000 gallon capacity)
- Household graywater recycling (GWR) (0-25 gallon capacity)
- Community stormwater recycling (CSW) (0-100,000 gallon capacity)
- Community graywater recycling (CGW) (0-180 gallon capacity)
- Community-scale water recycling facility (WRF) (0-9000 gallon capacity)

The energy and water storage technologies included in our case study are:

- Household rainwater tanks (RWTANK) (0-5000 gallon capacity)
- Community stormwater tanks (SWTANK) (0-100,000 gallon capacity)
- Household battery (IND-BAT) (0-60 KW unit capacity)
- Community-scale battery (COM-BAT) (0-500 KW unit capacity)

3.3.6 Resource demands

As indicated above, Pecan Street Inc. Dataport (2016) provides hourly, home-level electricity and water usage data for the year 2016 which we use to parameterize the demand profiles in our case study. After eliminating homes with significant missing data or data that appear unreliable, the dataset for our case study includes 32 homes. The data are cleaned by using the interquartile rule to determine and correct outliers; the rule states that any monthly water and electricity use value which is 1.5 times the difference between the first and third quartiles above or below the first or third quartile, respectively, is an outlier (Manikandan, 2011). After reviewing the data, we determine that any monthly electricity use below 200 kWh or above 2800 kWh is an outlier, and that any monthly water use below 6000 gallons or above 27,000 gallons is also an outlier. For each resource, all outliers below the minimum value are replaced by the first quartile value, and all outliers above the maximum value are replaced by the third quartile value.

3.3.7 Performance and cost data

Table 4.3 succinctly reports the main performance and cost assumptions for each technology in the model, including operational energy use and capital, fixed, and variable costs. The capacity limit for each technology was given in Section 4.3.5. The capital and fixed costs of all technologies (with exceptions noted below) are annualized by spreading their costs over ten years at a discount rate of 5%.

The fixed cost of a given technology is incurred whenever any positive amount of capacity is installed, and does not depend on the capacity. Mathematically, fixed costs are included in the formulation as costs multiplied by the integer purchase decision variables. For technologies whose investments are lumpy and are represented only by integer variables, the fixed cost represents the full upfront cost of installing that amount of capacity. For technologies whose investment can be continuous, the fixed cost still applies and is

Table 3.1. Main performance and cost assumptions for technologies in our case study, and documentation of data sources.

Technology	Capital Costs	Fixed Costs	Variable Costs	Energy Use	Sources
Utility Electricity	N/A	\$10	$\$0.08, 0.11, 0.13, 0.14, 0.16/kWh$	N/A	[36]
RFT-PV	\$722 / kW	\$2000	\$0	N/A	[66]
IND-BAT	\$500 / kW	\$80	N/A	0.01 kWh/hr	[67]
COM-PV	\$513 / kW	\$25,000	\$0	N/A	[66]
COM-BAT	\$500 / kW	\$80	N/A	0.01 kWh/hr	[67]
WIND	\$840 / kW	\$76,000	\$0	N/A	[174]
HBRD (2.5 MW)	N/A	\$5,000,000	N/A	N/A	[82]
Utility Water	N/A	\$8.6, 11, 17, 37, 38	\$2.89, 4.81, 8.34, 12.70, 14.39/kGal	N/A	[10]
RWH (5000 gallons)	N/A	\$1600	N/A	0.5 kWh/kL	[130], [170]
RWTANK	\$0.50 / gal	N/A	N/A	0.5 kWh/kL	[130]
GWR (25 gallons)	N/A	\$2300	N/A	1 kWh/kL	[130]
CSW (100,000 gallons)	N/A	\$251,900,000	N/A	5000 kWh/MGal	[130]
SWTANK	\$0.50 / gal	N/A	N/A	5000 kWh/MGal	[130]
CGW (180 gallons)	N/A	\$71,500	N/A	5000 kWh/MGal	[130]
WRF (9000 gallons)	N/A	\$900,000	N/A	15,000 kWh/MGal	[166]

complemented by the capacity-dependent capital cost. Fixed costs are spread across ten years with a discount factor of 5% except in the WRF case, where the annual cost is kept the same as in the case study of Vitter et al. (2018).

Given that some continuous amount of capacity is added, each unit of capacity is associated with a capital cost. Mathematically, the capital costs appear in the formulation as costs multiplied by continuous capacity installation variables. Capital costs are spread over ten years with a discount factor of 5%. Some technologies have seen very limited real-world deployment (e.g., WRF, HBRD) or are practically only available in discrete sizes (e.g., RWH, GWR), so they are represented as purely integer investments with fixed costs but no capital costs.

Variable costs are assessed according to the operating levels of technologies in the cost-minimizing dispatch solution determined by the model. There are five variable costs for utility electricity and utility water because they have rate structures with five different price tiers. In our results below, we label the five utility electricity tiers in ascending order as U_ELC1, U_ELC2, U_ELC3, U_ELC4, and U_ELC5, and the five utility water tiers similarly as U_H2O1, U_H2O2, U_H2O3, U_H2O4, and U_H2O5. It is important to note that the costs associated with electricity and water inputs to the technologies are not included in the variable cost parameters, because these costs are accounted for separately through utility purchases of these resources, or investments in the distributed technologies that produce them and make them available for final consumption or for other technologies to use. Operational energy use by technology is shown in Table 4.3, where batteries have some energy "use" because they do not perfectly maintain storage charge. Given this cost accounting, only utility purchases have variable costs.

3.3.8 Capacity factors and weather data

The Pecan Street Inc. Dataport (2016) dataset provides empirical time series of home-level RFT-PV generation. Using these time series and knowing the nameplate capacities of the corresponding units, we calculate a time series of average RFT-PV capacity factors in our case study community. For all daytime hours, the capacity factor for COM-PV is assumed to be greater than that for RFT-PV by 0.03 (in fractional terms). This captures the likely outcome that COM-PV is slightly more efficient due to superior siting, orientation, and electrical hardware (Fu et al., 2019). Capacity factors for wind technologies are calculated by taking Texas wind generation and dividing it by the total nameplate capacity of Texas wind turbines, where both empirical datasets are provided by the Electric Reliablity Council of Texas (2018). Capacity factors for the community wind-solar hybrid (HBRD) are computed by adding 0.015 to the COM-PV capacity factors due to the efficiencies gained by using the wind turbine inverter (Guterl, 2018), multiplying these numbers by 0.2 since solar panels only account for 20% of the capacity, and then adding these figures to the capacity factors of community WIND multiplied by 0.8.

The Pecan Street Inc. Dataport (2016) dataset also includes weather information. By combining its hourly rain data with the median home roof square footage of 1959 square feet (also from the Pecan Street Inc. Dataport (2016) dataset), we are able to determine the amount of rainwater available to each home every hour. These data are important due to the availability of the RWH technology. We also assume that each household uses 30% of its total water demand for outdoor uses like irrigation which can be satisfied with graywater (this is the only use for graywater) (Awal et al., 2019), and that 80% of each household's used water is available for water recycling (Vitter et al., 2018).

3.3.9 Carbon emissions

All DETs and DWTs in our case study do not produce carbon emissions. However, utility electricity and water purchases do have carbon footprints. The utilities are used to supplement DET and DWT production, and in the case of DWTs, utility electricity can be used to power the technologies (with associated carbon emissions) even though DWTs do not produce carbon emissions on their own. Given the solution determined by the model, we can use data from the local utilities to calculate the total carbon footprint of satisfying the households' electricity and water demands for one year.

Austin Energy (2019) indicates that the average carbon intensity of its electricity during the year 2018 (the most recent available estimate) was 0.85 lbs CO_2/kWh. Therefore, multiplying this average carbon intensity by the quantity of electricity purchased from the utility yields the total carbon emissions associated with electricity provision. While there are emissions embedded in the manufacturing and distribution supply chain for DETs, these are orders of magnitude lower than the direct emissions resulting from fossil fuel power plant operations in the bulk power system (Pehl et al., 2017), so we exclude embedded emissions from this study.

In 2018, Austin Water (2019b) required 1723-2286 kWh/Mgal (0.46-0.63 kWh/kL) with an average of 1920 kWh/Mgal to treat water withdrawn from the Colorado River to drinking standards and pump it to end users. Therefore, multiplying this average energy intensity of water treatment and pumping by the quantity of water purchased from the utility yields the total energy use associated with utility water provision. Similarly, wastewater treatment and return to the Colorado River required 1305-2660 kWh/Mgal (0.34–0.70 kWh/kL) with an average of 1924 kWh/Mgal. This energy intensity for wastewater treatment is multiplied by the total volume of wastewater that the households send back to the central water utility to yield more energy use associated with water. Since it is assumed that the water utility receives all of its energy from the electric utility, the water utility's energy use for water treatment, pumping, and wastewater treatment is multiplied by the same carbon intensity of electricity provided in the preceding paragraph, to determine the carbon emissions for utility water services.[2]

3.4 Scenarios

For our Austin case study, we consider 17 different scenarios that are distinguished by their optimization scheme (i.e., whether DETs and/or DWTs can be added) and level of aggregation (i.e., whether optimal decisions are made by individual households or communities of varying size). These scenarios are designed to help us address our primary

[2]Note that one wastewater treatment plant operated by Austin Water produces biogas for a combined heat and power (CHP) plant, which in turn provides electricity for the wastewater plant. This CHP plant is owned by Austin Energy and its emissions are included in the average carbon intensity for Austin Energy (Bogusch and Grubbs, 2014).

research questions and hypotheses. Specifically, we are interested in understanding whether DET and DWT investments are economically justified given current data, whether co-optimizing these investments as an integrated DEWS improves economic competitiveness, and whether community-scale aggregation favors greater DEWS adoption.

City of Austin (2019) and Austin Water (2019a) do not allow electricity or water bought from the utility or generated behind the meter to be shared across homes, though in some cases distributed electricity generation can be sold back to the utility. In our scenarios, we enforce this prohibition on transferring utility-supplied resources from home to home, and we do not allow distributed electricity and water outputs to be sold to the utilities. However, in the scenarios with community aggregation, we allow resources produced by community-scale DETs and DWTs to be dispatched to any home within the community. Since the objective of the optimization problem is to minimize the total cost of satisfying all households' electricity and water demands, the model will tend to dispatch community-scale resources to the homes with higher consumption levels, since they face higher tiered rates on the margin. Implicitly, our assumption is that the households in the community could conduct their own monetary transfers to remedy any perceived unfairness of this approach and ensure that it yields a Pareto improvement where everyone's bill is reduced. Note that the outputs of home-level DETs and DWTs cannot be shared across homes.

To investigate the effects of co-optimizing electricity and water investments in an integrated DEWS, we compare scenarios where the model can invest in both DETs and DWTs to other cases where the model can only deploy one of these groups of technologies. To explore how the community could most cost-effectively meet its electricity and water demands with limited reliance on central utilities, we solve a number of Limited Utility scenarios. In these scenarios, monthly household electricity purchases are limited to the first tier of the rate structure (500 kWh) (City of Austin, 2019) and water purchases are limited to the first four tiers (20 kGal) (Austin Water, 2019b). Four tiers of the water rate structure are included because this is the lowest tier in which the majority of households could produce enough water to meet their demands every month. However, we relax this water restriction slightly further to 21 kGal/month for two households in the dataset whose water consumption is particularly large, so that their demand can be met by the model even with home-scale rainwater and graywater technologies.

Our scenario set is comprised of all combinations of the following five optimization schemes and four aggregation levels. There are in fact 17 scenarios instead of 20 because the aggregation level is irrelevant with the Utility Only optimization scheme. Given that there are 32 unique homes in the dataset, the community aggregation scenarios with 320 and 3200 homes assume that there are 10 and 100 identical homes, respectively, corresponding to each unique home in the dataset. By scaling up the size of the community, we can see whether a higher level of aggregation favors investments in distributed technologies.

The five optimization schemes are:

- ***Co-Optimized*** – Can invest in both DETs and DWTs and/or use the utilities
- ***Electricity Only*** – Can only invest in DETs and/or use the utilities
- ***Water Only*** – Can only invest in DWTs and/or use the utilities
- ***Utility Only*** – No DET or DWT investments are allowed and all demands must be satisfied using the utilities
- ***Limited Utility*** – The Co-Optimized scenario with additional restrictions that limit utility purchases to less than 500 kWh/month and 20 kGal/month per household

The four aggregation levels are:

- ***Individual*** – A group of 32 households make investment and dispatch decisions individually, and their results are aggregated
- ***32 houses*** – A group of 32 households optimize their distributed technologies as a collective unit, but do not share utility electricity or water

- ***320 houses*** – A group of 320 households optimize their distributed technologies as a collective unit, but do not share utility electricity or water
- ***3200 houses*** – A group of 3200 households optimize their distributed technologies as a collective unit, but do not share utility electricity or water

3.5 Results

In this section we present, compare, and discuss results from our scenarios which combine different optimization schemes and aggregation levels. We begin by comparing the annualized investment and operating costs of satisfying electricity and water demands across all scenarios. Then we examine how the technologies used to provide electricity and water vary by aggregation level and across the hours in a year. Finally, we explore the implications of co-optimizing DET and DWT investments rather than investing in just one group of technologies.

3.5.1 Costs and fraction of demand met by technology

Fig. 3.1 displays the average annualized cost of satisfying all electricity and water demands in each scenario. It also shows the fractions of electricity and water that are supplied using distributed technologies instead of central utilities. The height of each bar is equivalent to the minimized objective value given in Dollars (see left y-axis) divided by the total number of households in a given scenario. The height of each dot represents the DET electricity production divided by total electricity production; this is labeled as the *Electricity Fraction* and corresponds to the right y-axis. The height of each triangle represents the DWT water production divided by total water production; this is labeled as the *Water Fraction* and also corresponds to the right y-axis. Note that, since the electricity and water fractions represent the amount of electricity and water produced by distributed technologies over total production, their numerators and denominators both include production that gets curtailed, is sent to storage, or is lost while being stored. Each subfigure in Fig. 3.1 corresponds to an optimization scheme. Within each subfigure, the green bar at the far left (which is the same in all subfigures) is the Utility Only baseline, while the other bars represent different aggregation levels.

The annualized costs for all scenarios are lower than the cost in the Utility Only scenario, with the exception of the scenario with Individual aggregation and the Limited Utility scheme. This is intuitive, because in all scenarios except those with the Limited Utility scheme, the Utility Only solution is feasible, and therefore the model can only improve upon its solution. However, the restrictions on utility purchases in the Limited Utility scheme make the Utility Only solution infeasible, and with households optimizing individually, the annualized cost increases as a result of replacing utility purchases with DETs and DWTs. Nevertheless, the fact that costs are almost always lower than the Utility Only baseline indicates that at least some DET and DWT investments are economically competitive.

The Electricity Only scenarios, which only allow DET investments and use of the utilities, yield small savings relative to the Utility Only baseline. These savings slowly increase with the level of aggregation. The Water Only scenarios, which only allow DWT investments and use of the utilities, yield larger savings than the Electricity Only scenarios at all levels of aggregation, implying that DWTs offer greater economic benefits than DETs within this sample of homes. As expected, the Co-Optimized scenarios, which allow investments in DETs and DWTs and use of the utilities, lead to the largest cost savings at every level of aggregation. Meanwhile, the Limited Utility scenarios result in the smallest savings. In line with previously described logic, the additional constraints in the Limited Utility scenarios are binding and cause the model to invest in more distributed technologies than would otherwise be justified economically.

The *Electricity Fraction* and *Water Fraction* generally increase with the level of aggregation, with the exception of the *Electricity Fraction* over the transition from the

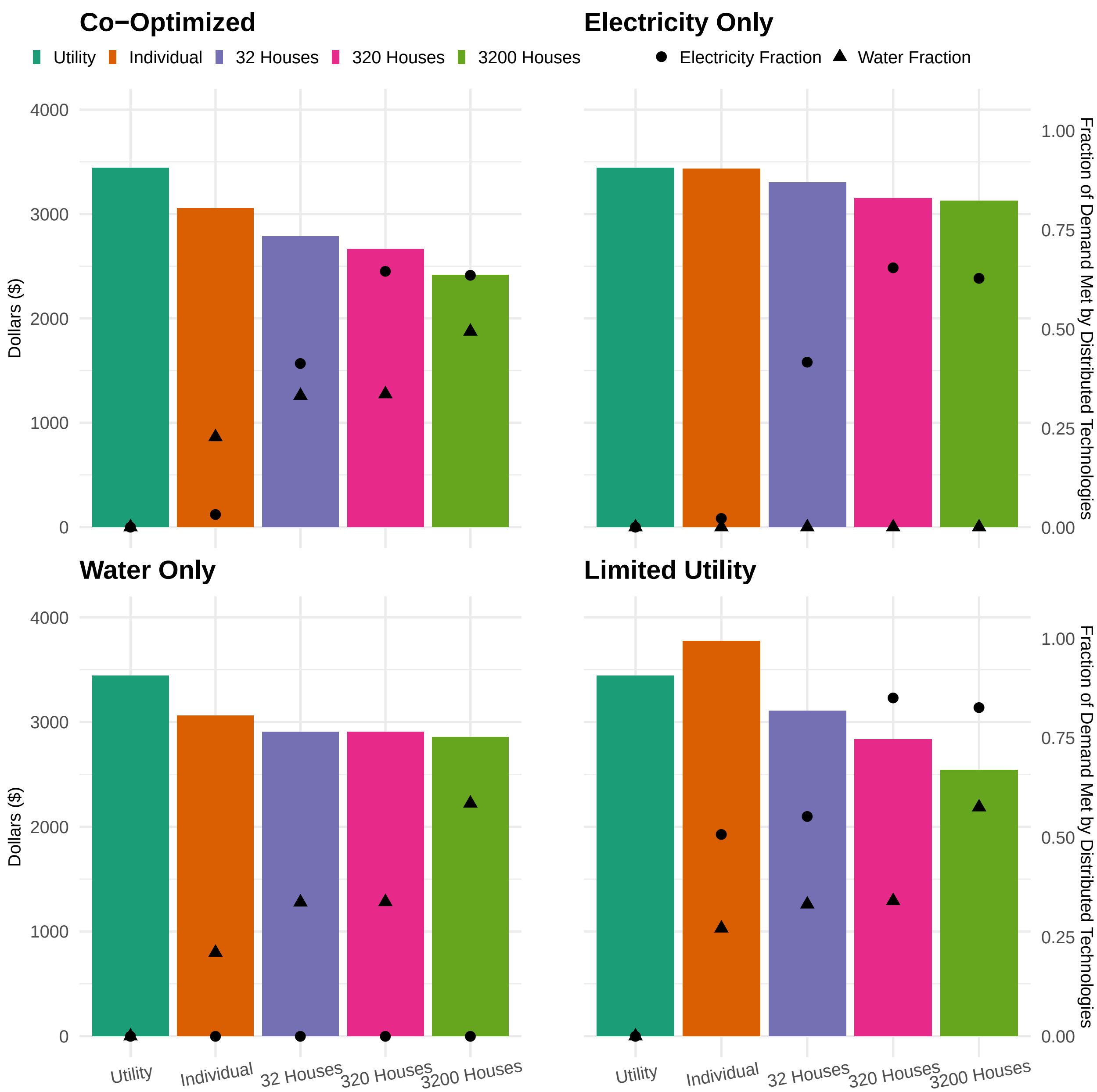

Figure 3.1. Comparison of average annualized cost (per household) and fractions of electricity and water produced by distributed technologies, across the scenarios.

320 Houses aggregation level to the 3200 Houses level. The general increasing trend is intuitive because as the aggregation level expands, the costs are shared across more households and economies of scale enhance the case for investment. We interpret the slight declines in *Electricity Fraction* from 320 Houses to 3200 Houses as artifacts of some of the lumpy investment decisions in the model, where certain technologies are available only in discrete sizes (this effect is explored further in Figs. 3.6 and 3.7). The *Water Fractions* for the Water Only, Co-Optimized, and Limited Utility schemes are nearly identical at each aggregation level. In contrast, the *Electricity Fractions* for the Electricity Only, Co-Optimized, and Limited Utility schemes vary more significantly for a given aggregation level. The Limited Utility scenarios have the largest *Electricity Fractions* for all aggregation levels and, interestingly, the Electricity Only scenarios have higher *Electricity Fractions* than the Co-Optimized scenarios at all levels of aggregation except Individual. In other words, the Co-Optimized scheme often invests less in DETs than the Electricity Only scheme. The reasoning is essentially that the option of purchasing all resources from the utilities implies a limited budget that could ever be justified for expenditures on distributed technologies; given that the Co-Optimized scenarios also include investment in DWTs, less of the implicit budget is available for DET additions.

Economically, co-optimizing electricity and water as an integrated DEWS leads to the greatest cost savings. However, the sum of the Electricity Only and Water Only scenarios' savings exceeds the Co-Optimized scenario's savings at each level of aggregation except for 3200 Houses. At the 3200 Houses aggregation level, co-optimizing exploits synergies between DETs and DWTs to amplify the economic benefits that each group of technologies could achieve individually. In other words, the benefits of co-optimization increase with the level of aggregation. With more homes demanding electricity and water, the implied budget available for distributed technology investments is larger, and the pooling of more heterogeneous resource and demand profiles offers more significant opportunities to improve system economics through synchronized dispatch.

3.5.2 Production of electricity and water

3.5.2.1 Annual production of electricity and water

The average yearly electricity production by technology and the average yearly water production by technology for all scenarios are shown in Figs. 3.2 and 3.3, respectively. The height of each bar corresponds to the kWh of produced electricity or the gallons of produced water divided by the number of households in a given scenario. Note that, to reflect actual demand, curtailed electricity has been removed but there is never any curtailed water. The different colors correspond to different technologies and the charts compare a given scheme and its corresponding aggregation levels to the Utility Only baseline. The Water Only scenarios are excluded from Fig. 3.2 because they do not allow DET investments and the Electricity Only scenarios are excluded from Fig. 3.3 because they do not allow DWT investments.

Household graywater recycling (GWR) and household rainwater harvesting (RWH) satisfy some of the water demand for all scenarios shown in Fig. 3.3 (other than Utility Only). The contributions of GWR and RWH technologies are fairly similar across optimization schemes and aggregation levels. However, the water recycling facility (WRF) is only added in the scenarios with 3200 Houses. The WRF is assumed to be a lumpy investment with a specific, predefined size, consistent with the notion that it requires a certain scale in order to be viable. This is the case with 3200 Houses, but not at lower levels of aggregation.

Household rooftop photovoltaic panels (RFT-PV) satisfy some electricity demand at the Individual aggregation level for the scenarios shown in Fig. 3.2, with the Limited Utility scheme producing the most RFT-PV electricity and the Electricity Only and Co-Optimized schemes producing only small amounts. For the 32 Houses aggregation level, community-scale photovoltaic panels (COM-PV) replace RFT-PV, and at higher aggregation levels the

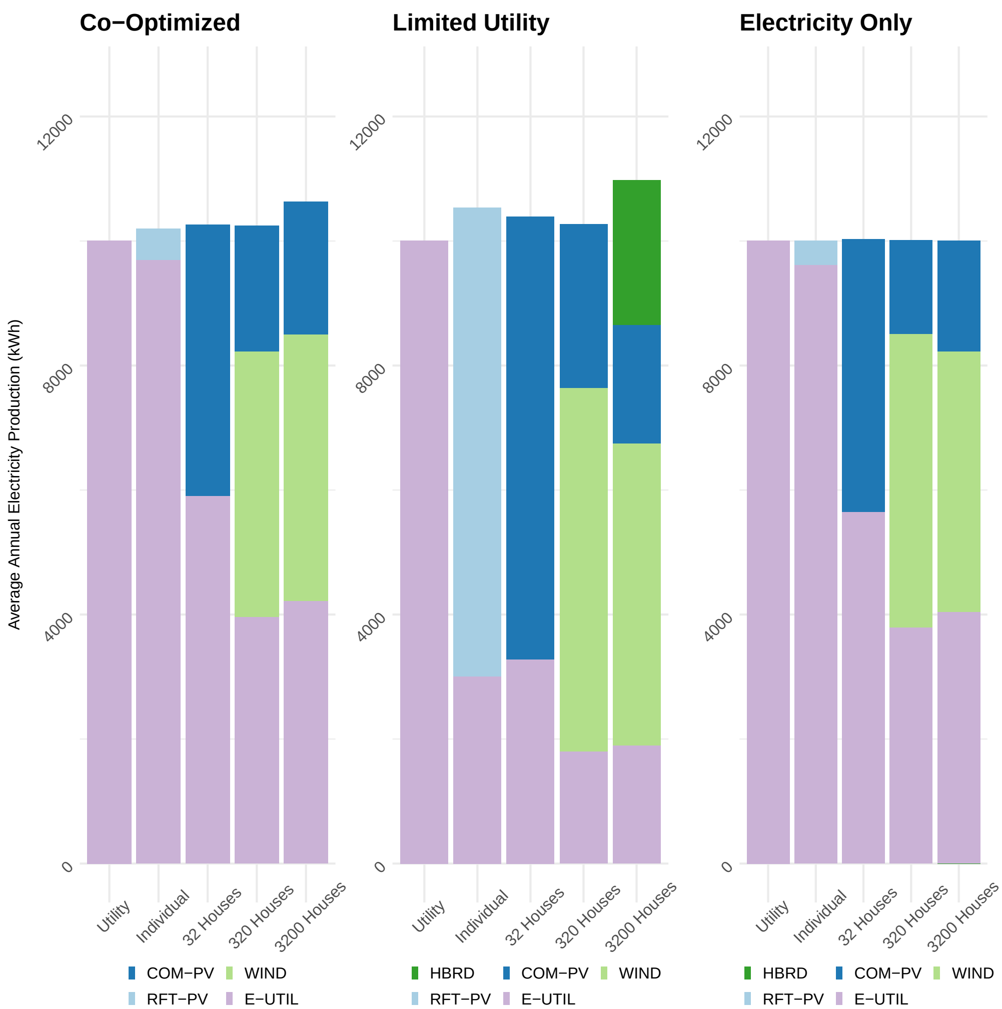

Figure 3.2. Comparison of average annual electricity production by technology across the scenarios.

scenarios use a combination of COM-PV and wind turbines (WIND) with WIND producing a majority of the total electricity. The Limited Utility scheme also invests in the wind and solar hyrbid system (HBRD) for the 3200 Houses aggregation level. The total amount of electricity produced increases as DET investment increases, and the amount of electricity produced by DETs increases with the aggregation level. These results suggest that home-

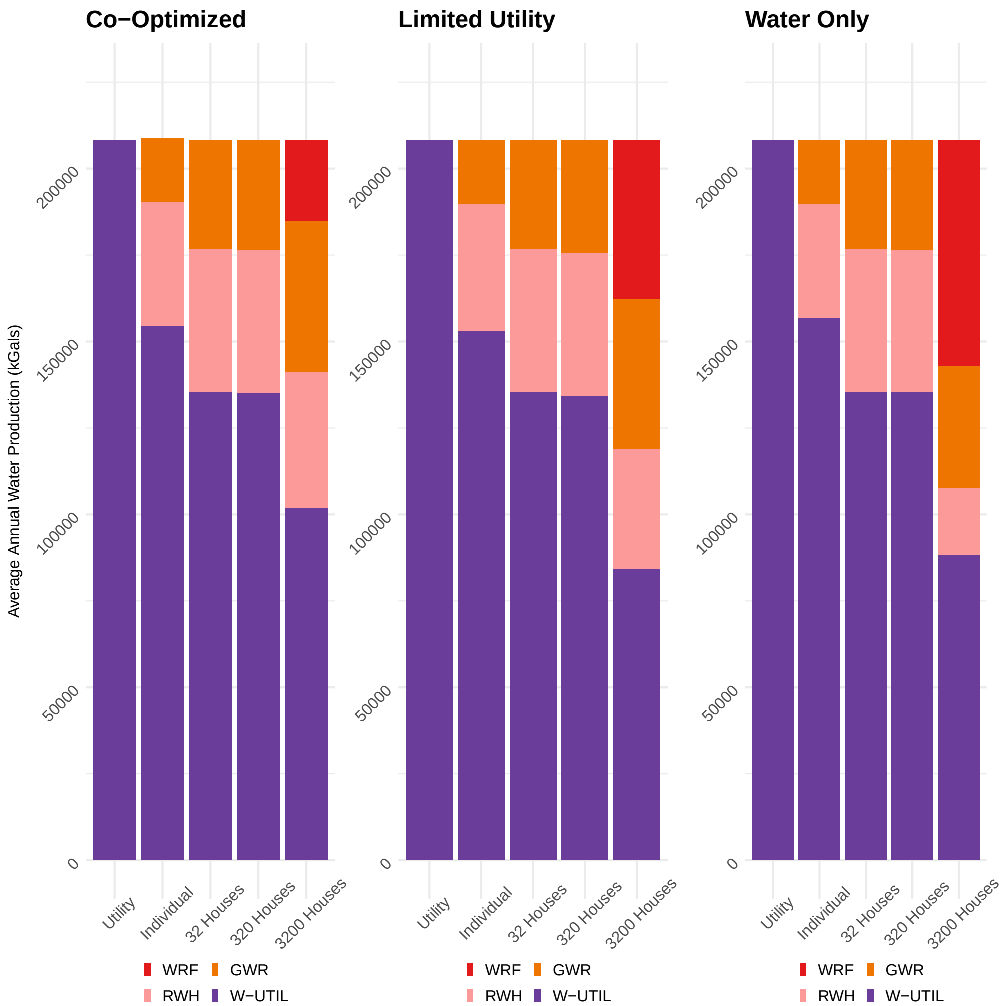

Figure 3.3. Comparison of average annual water production by technology across the scenarios.

level RFT-PV is economically justified only on a small scale, whereas community-scale DET investments (COM-PV, WIND, HBRD) are much more economically attractive and could displace significantly more utility electricity.

The bars in Fig. 3.2 do not all have equal heights because certain DWTs require additional energy in order to operate. This is clearly seen by comparing the Co-Optimized and Limited Utility scenarios, which allow investments in DETs and DWTs, to the Electricity Only scenarios. The Electricity Only scenarios do not feature endogenous electricity demand added by DWTs, and as a result all of their bars are of equal height. Furthermore, because the Limited Utility scenarios place a strict upper limit on the electricity that can be purchased from the utility, they all include greater electricity production from DETs than the scenarios with the other optimization schemes. Even with the mandate to produce more distributed electricity, the HBRD installation is only deployed in the Limited Utility scenario with 3200 Houses. Similar to the analogous result for the WRF, the lumpy HBRD investment requires this critical community scale in order to become economically viable.

3.5.2.2 Monthly production of electricity and water

Since resource availability and electricity and water demands vary throughout the year, it is informative to investigate differences in the composition of electricity and water production on a more granular timescale.

The stacked bar charts in Figs. 3.4 and 3.5 depict the total production of electricity and water, respectively, by technology in each month of the year for the Co-Optimized scheme and different community aggregation levels. The height of each bar measures the total kWh or gallons produced in each month, excluding any curtailed production. Note that, unlike in previous figures, the height of the bar corresponds to the total amount of electricity or water produced by all households in the scenario, not the average household's amount. Therefore, the y-axis scale increases by an order of magnitude with each jump in aggregation level from 32 to 320 to 3200 Houses.

The monthly bar heights in Figs. 3.4 and 3.5 reflect the variations in demands for electricity and water throughout the year. Electricity demand exhibits much sharper seasonality than water demand, and is more than twice as high in the peak summer month

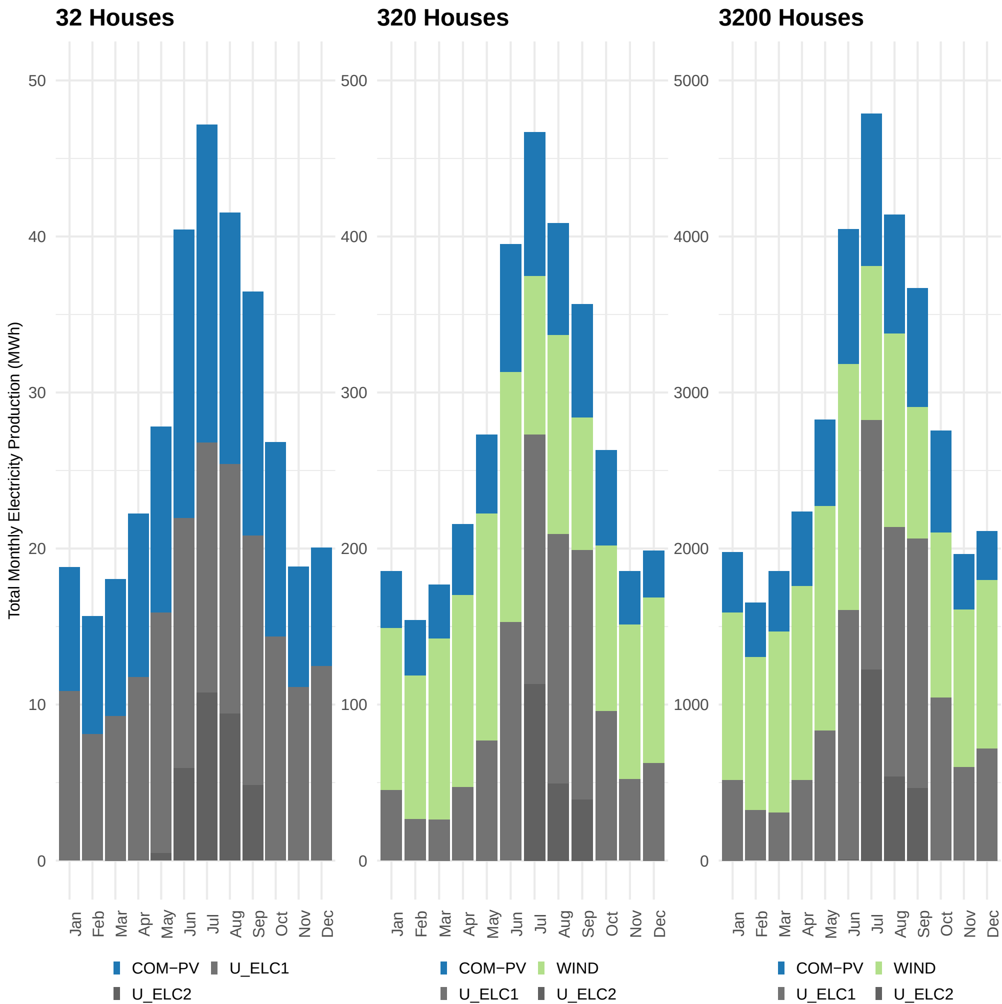

Figure 3.4. Comparison of monthly electricity production by technology for different community aggregation levels, under the Co-Optimized scheme.

than in the lowest winter month due to strong summer air conditioning demand in Texas that drives the peak residential load. In most months of the year, utility electricity purchases are limited to the first tier of the rate structure. However, during the summer months, some utility electricity in the second tier is purchased to help satisfy peak loads. Effectively, the ability to purchase electricity from the utility – even at marginally increasing rates – acts

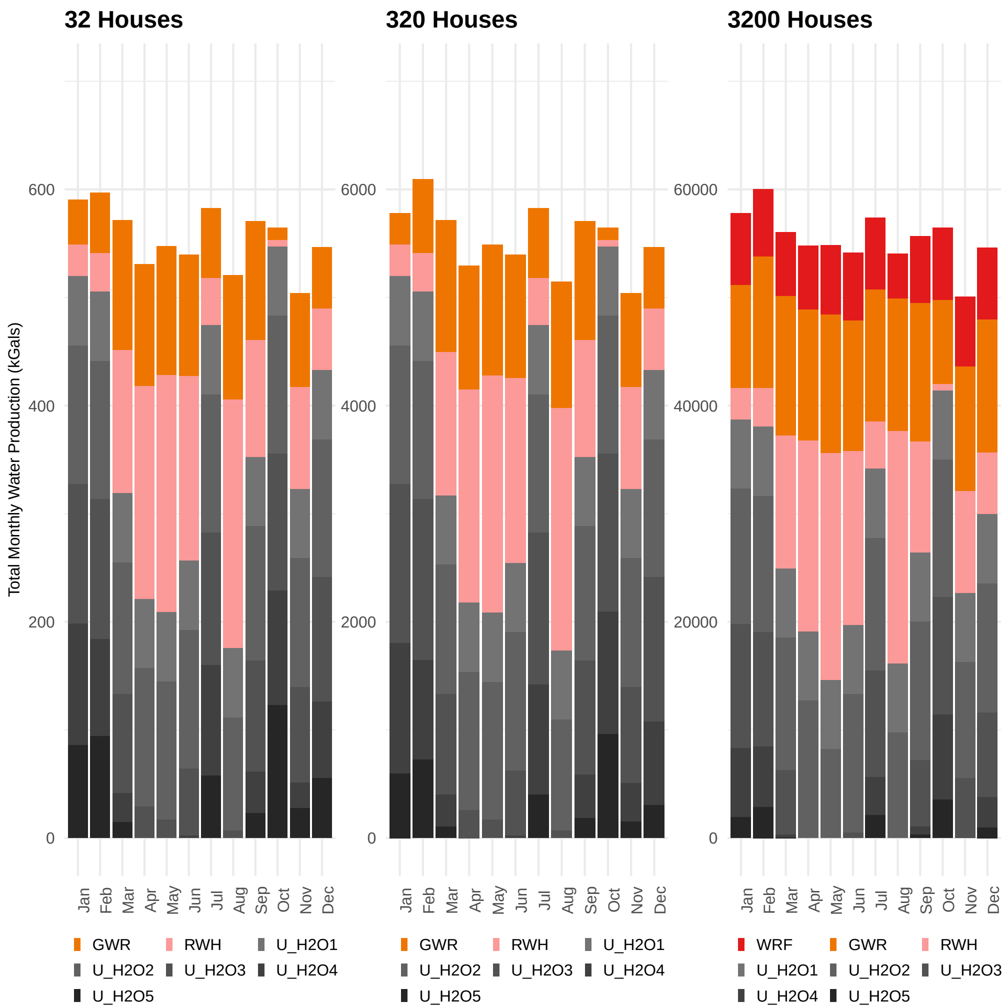

Figure 3.5. Comparison of monthly water production by technology for different community aggregation levels, under the Co-Optimized scheme.

as a backstop that prevents the model from having to size DET investments for peak load conditions and have them be underutilized at all other times.

In addition to the monthly variations in demands, Figs. 3.4 and 3.5 also illustrate how distributed resource supplies change from month to month. COM-PV generation is higher in the summer months than in the winter months, which is well aligned with the electricity demand pattern. On the other hand, WIND production is higher in the winter, so it tends to be more abundant during parts of the year when less electricity is needed. Monthly water demand is relatively constant throughout the year, but rainfall peaks in the spring with another high point in August. This is clearly visible for the pink bars which represent the rainwater harvesting (RWH) technology in Fig. 3.5. During these months with abundant rainfall to harvest, significantly less water has to be obtained from the utility. However, in months with limited rainfall, whitewater demand must be satisfied using utility water from higher price tiers. Since the fixed costs for being in these higher utility water tiers will be incurred anyway, the model finds it cheaper to continue purchasing from the utility to meet its graywater demand rather than use electricity to recycle the graywater produced within the home. This effect is most clearly illustrated by the October results in Fig. 3.5, when there are only 0.1456 inches of rain and the solutions for 32 and 320 Houses feature very little RWH or GWR production. However, at the 3200 Houses level of aggregation where whitewater can be produced by the WRF even in the absence of RWH production, GWR production returns to a normal level.

3.5.2.3 Average installed capacity per household

Average (per household) DET and DWT capacity additions for all scenarios are shown in Figs. 3.6 and 3.7, respectively. Within the figures, the bar chart for each scenario includes one bar for generation capacity and a second bar for storage capacity, with each bar broken down into the different technologies that are installed.

As the aggregation level expands, per-household DWT production capacity additions consistently decrease for all optimization schemes in Fig. 3.7. As we have seen, DWT investments such as the GWR and RWH technologies are economically competitive even at the Individual home level, so community aggregation is not required to incentivize adoption

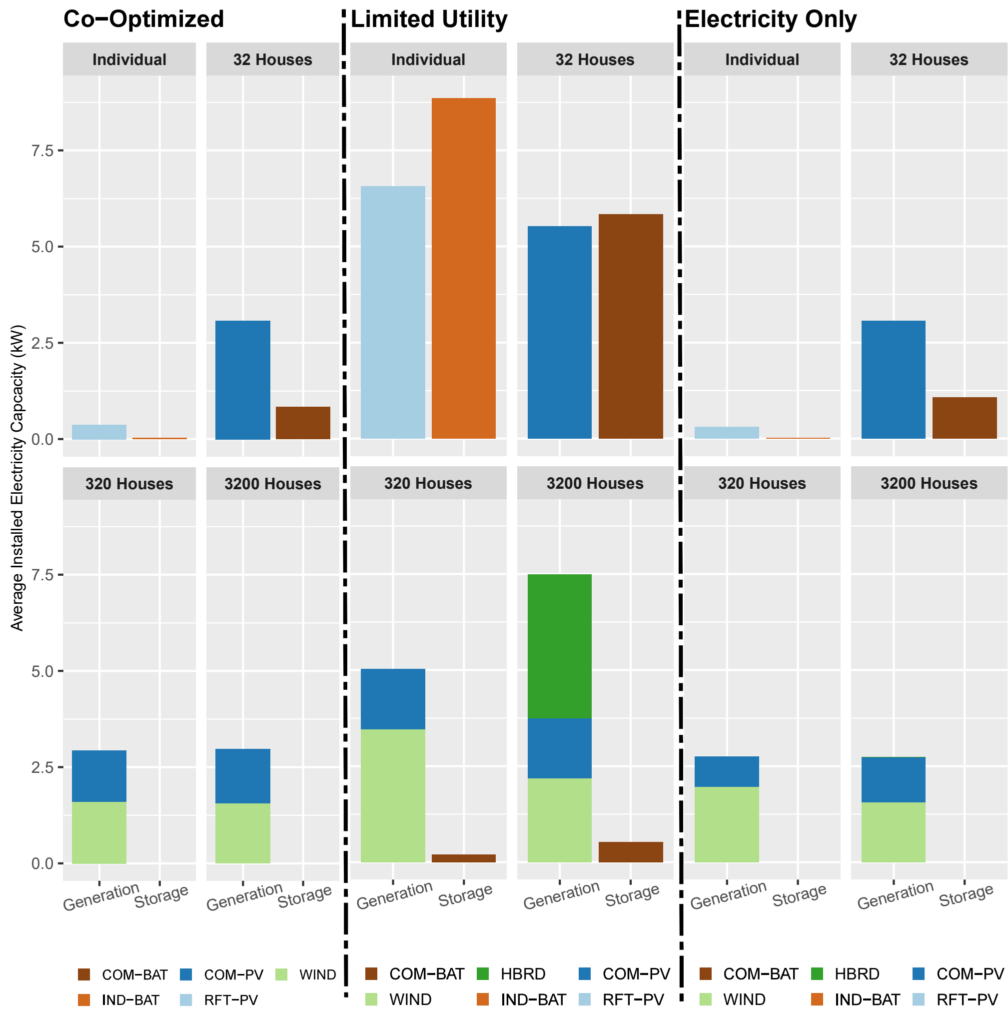

Figure 3.6. Average installed DET capacity by technology across scenarios. In each bar chart, the first bar depicts generation technologies and the second bar depicts storage technologies.

(except for the WRF at 3200 Houses). As the aggregation level becomes larger, the DWTs can operate more efficiently, so less new capacity is required per household even though the *Water Fraction* supplied by DWT generation actually increases. The relationship between aggregation level and average DET generation capacity additions is not monotonic for any of the three optimization schemes in Fig. 3.6. For the Co-Optimized and Electricity Only schemes, DET generation deployment increases from Individual to 32 Houses, then decreases. At low levels of aggregation, community-scale investment makes certain DET technologies much more economically desirable, leading to greater deployment of COM-PV at 32 Houses than RFT-PV in the Individual case. At high levels of aggregation, system efficiency gains become the dominant factor and less new DET generation capacity is required even though the *Electricity Fraction* supplied by DETs actually increases in some scenarios.

For the Limited Utility scheme, there is eventually an uptick in DET generation capacity at 3200 Houses, when the decision is made to invest in the HBRD facility. This is an example where the lumpy nature of the investment means that there is a sudden jump in the use of DETs to generate electricity, when the community becomes large enough to economically justify the installation of a relatively large, shared facility. The Limited Utility scenario with 3200 Houses also demonstrates the interdependence between distributed electricity and water systems. On the water side, the model chooses to add the WRF in this scenario, which needs considerable electricity in order to operate. The Limited Utility scheme prevents the model from obtaining all of this additional electricity from the utility, so it must invest in substantially more DET generation capacity in order to provide electricity for the WRF. The decision to invest in the HBRD facility meets this demand.

Battery electricity storage is expensive, so it is informative to establish the conditions under which battery investment is included in the optimal solution. From Fig. 3.6, it is interesting that very little home-level battery storage is ever added (with the one major exception of the Limited Utility scheme and Individual homes), whereas substantial community-scale battery storage is deployed in a wider variety of scenarios. Batteries are essentially modular, so that per-unit upfront costs do not decline significantly with the size of the installation. However, the major advantage of community-scale battery storage is that it can take advantage of the heterogeneous distributed resources and demand profiles of

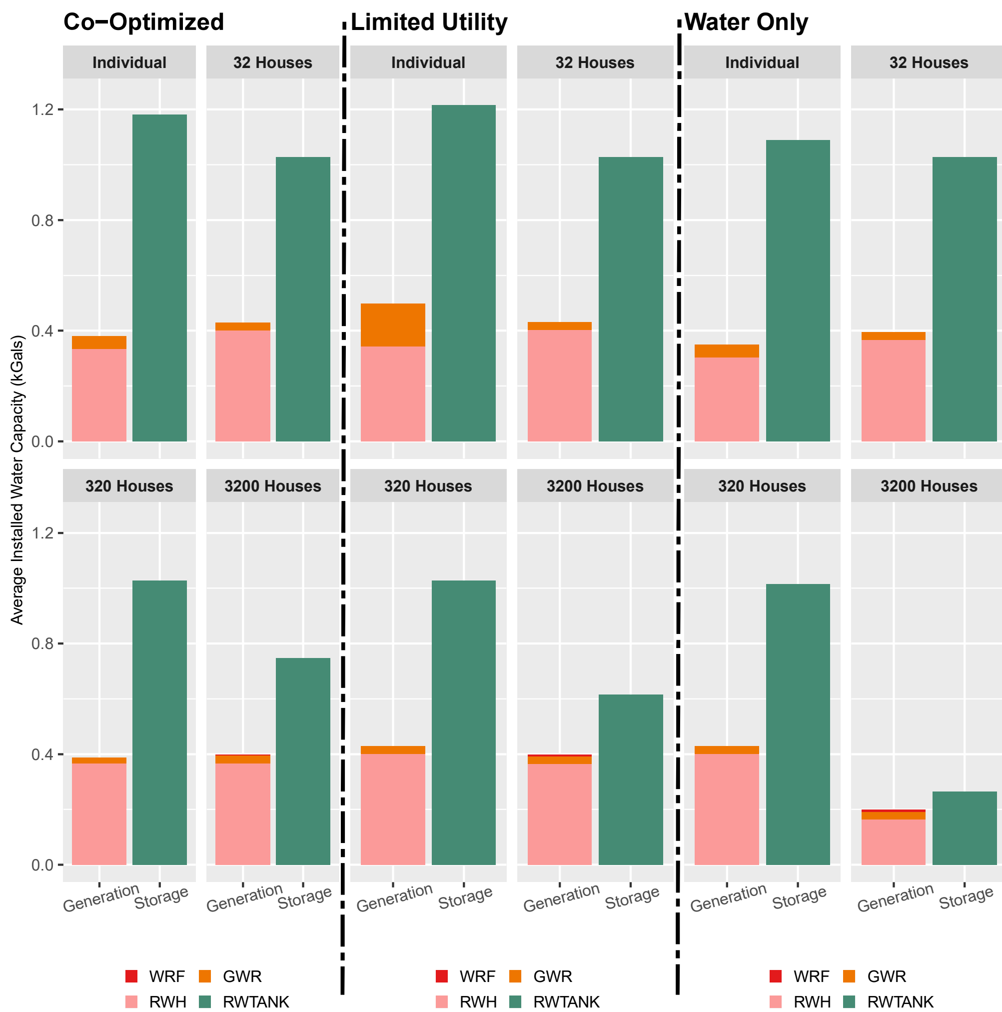

Figure 3.7. Average installed DWT capacity by technology across scenarios. In each bar chart, the first bar depicts generation technologies and the second bar depicts storage technologies.

homes in the community to charge from or discharge to different points at different times. In other words, compared to an individual home battery, a community-scale battery unit has more options for charging from generators or discharging to satisfy loads. It is also clear that having a balance between solar PV and wind resources in the DET generation mix sharply reduces (or eliminates) the role for battery storage. Solar PV and wind resources have complementary capacity factor profiles, with the former active during the day and the latter peaking at night. As long as utility purchases are not constrained, it is evidently less costly to support a balanced portfolio of distributed solar and wind assets with occasional utility purchases than with battery storage investments. If the DET portfolio leans heavily toward solar, however, then battery storage is an economically competitive strategy for mitigating the total lack of solar power at night.

On the other hand, water storage is comparatively cheap, and all the scenarios in Fig. 3.7 incorporate household rainwater tanks (RWTANK) into their optimal solutions. Additions of RWTANK per household are fairly steady across the scenarios, until they drop considerably in moving from the 320 Houses to the 3200 Houses aggregation level. This is a direct consequence of the model deciding to invest in the WRF at the 3200 Houses level. The WRF recycles used water and returns it to the households to be used again, which reduces the need for new water supplies entering the community from the central utility or in the form of rainwater. This effect is particularly visible in the Water Only scenario with 3200 Houses, where the installed RWH capacity also declines significantly from its value with 320 Houses.

3.5.3 Carbon emissions

Average carbon emissions per household for the Co-Optimized, Electricity Only, and Water Only scenarios are shown in Fig. 3.8. The height of each bar represents the average annual household emissions in metric tons of carbon dioxide for the given scenario. The two colors in each bar distinguish emissions associated with electricity and water obtained from the utilities. The first bar in each chart represents the Utility Only baseline and the remaining bars represent different levels of aggregation.

The striking finding that is immediately visible in Fig. 3.8 is that a Co-Optimized DEWS always reduces carbon emissions (in some cases substantially), while only investing in DWTs and sourcing their electricity inputs from the electric utility always increases emissions. The essential logic is that DWTs add more electricity use to the system, and as small-scale technologies, they typically operate less efficiently than the centralized water infrastructure. This result is consistent with the findings of Vitter et al. (2018), who effectively only considered Water Only scenarios in their study. However, if DWTs receive their electricity from carbon-free DETs such as solar PV panels and wind turbines, the water they produce will have a lower carbon footprint than water purchased from the water utility even if the DWTs are less energy-efficient. These carbon reductions associated with water only add to the emissions savings realized in electricity directly by substituting carbon-free distributed generation for electricity obtained from the grid.

Looking at the Co-Optimized scenarios, the emissions reduction becomes much larger as the aggregation level increases. This is because community-scale aggregation is required to make most of the DET generation options other than RFT-PV (which is quite expensive) economically viable, leading to investment in COM-PV, WIND, and eventually the HBRD facility.

Total carbon emissions in the Electricity Only scenarios are very similar to their levels in the Co-Optimized scenarios. The Electricity Only scenarios have higher water emissions, slightly lower (within 5% or less) electricity emissions because there are no DWTs demanding electricity, and nearly identical total emissions (within 1% or less). Interestingly, the Co-Optimized scheme yields slightly lower total carbon emissions than Electricity Only at the 3200 Houses aggregation level, but slightly higher emissions at the 32 and 320 Houses levels. While the differences are tiny, this further highlights the tradeoff between the lower efficiencies of DWTs but their ability to operate synergistically with carbon-free DETs, resulting in greater benefits of co-optimization at higher levels of community aggregation where DETs become more desirable investments.

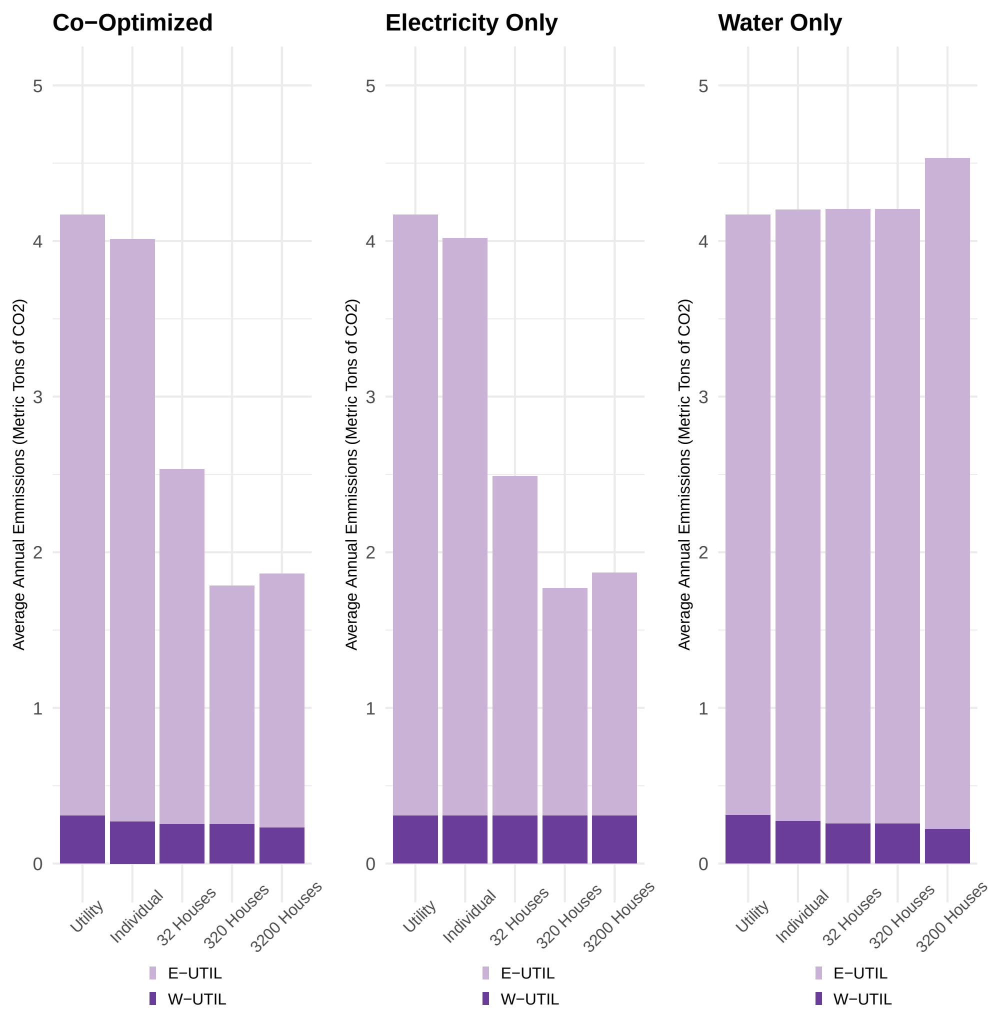

Figure 3.8. Average annual household carbon emissions by resource in the Co-Optimized, Electricity Only, and Water Only scenarios.

It is important to keep in mind that none of our scenarios includes any explicit constraint on carbon emissions or financial incentive to reduce emissions. The results plotted in Fig. 3.8 arise simply as features of the cost-minimizing solutions identified by the model in each scenario. Certainly, the results suggest that co-optimizing DET and DWT investments and operations, and aggregating these decisions at the community scale, can simultaneously reduce households' electricity and water costs as well as the carbon footprints associated with consumption of these resources.

3.6 Conclusions

3.6.1 The cost of investing in distributed technologies

A number of distributed electricity and water technologies are economically competitive at today's prices, and the case for investment is even stronger if DETs and DWTs can be co-optimized to form an integrated DEWS. The resulting cost savings increase when decisions are made and distributed technologies are shared by larger communities of households that pool resources. Limiting purchases of utility electricity and water only increases the cost compared to the the utility only scenarios when households are limited to home-scale distributed technologies. For all other levels of aggregation, it is still cheaper to use distributed technologies than it would be to use only utilities to satisfy demand. This implies that investing in distributed technologies is beneficial even in areas where utilities are fairly cheap and especially in areas where they are strained by rising demand.

3.6.2 Effects of aggregation

The electricity or water produced by, and the fraction of demand met by, distributed technologies generally increase with the aggregation level while the average capacity additions needed to do so decrease. This is intuitive because as more households pool their resources, they can spread fixed costs over more households, take advantage of lower per-unit costs stemming from economies of scale, and justify large and discrete installations. However, these trends do not always hold, due to the introduction of new energy-intensive water technologies that significantly increase energy demand or because the investment decision reaches a disjoint point where a significant capital investment would be needed to meet more demand with additional distributed technology capacity.

Furthermore, community-scale aggregation of distributed resources enables several other mechanisms that reduce costs. Community-scale resources can be intelligently dispatched to the households who pay higher marginal rates for utility electricity and water, which reduces the overall utility bills owed by the community. By itself this setup would be unfair to households who consume lower quantities of electricity and water, but a Pareto improvement could easily be realized through side payments. In addition, compared to home-level distributed technologies, a community-scale DEWS takes advantage of heterogeneous resource and demand profiles to achieve higher utilization rates of installed capacities.

3.6.3 Effects of co-optimization

When solving under the Co-Optimization scheme, for most levels of aggregation, it is not optimal to combine the optimal DWT capacity investments of the Water Only scheme with the optimal DET capacity investments of the Electricity Only scheme. So, the model chooses the best combination which by definition must be less costly than the sum of the two independent solutions, implying that there is a maximum "budget" that can be spent on distributed technologies. However, for the 3200 Houses aggregation level, there are enough houses to increase the "budget" so that the model can invest in both optimal capacities. Nonetheless, the model invests in a slightly different mix than simply the combination of the Electricity Only and Water Only schemes' investments that maximizes the benefits of both at a lower cost; this shows that the largest benefits of co-optimization arise at higher levels of aggregation.

Furthermore, co-optimizing balances the energy demand increase from DWT technologies with the carbon intensity reductions of DET technologies. This allows a community to benefit from the cost savings of DWT technologies and still reduce emissions via DET technologies.

3.6.4 Limitations

An MILP is much more computationally demanding than a simple linear program with only continuous variables. This forced us to model hourly dispatch for only one year, whereas over a multi-year timeframe, conditions for demands, sunlight, wind, and rainfall will vary from year to year. Furthermore, the constraint eliminating household-to-household sharing of resources purchased from the utilities also increased computational time. We did not regulate how the distributed technologies are shared. As a result of the scheme, the program sends more distributed technology production to higher usage customers than lower usage customers, creating equity issues that the community would need to address via transfers between households in order to realize a Pareto improvement.

We ignored costs associated with physically distributing community-scale resources to individual households, except for the WRF technology, where this cost was built into the input data we used. Since we are optimizing at the community scale, the assumption that the grid is already designed for two-way flow at least at the local level could be an acceptable assumption; however, in certain situations that could lead to dramatic underestimations of the total cost of distributed resources. However, ignoring distribution limits the insights that can be gleaned from this model, as creating and managing a feasible distribution system is one of the impediments for community-scale technology adoption. Furthermore, in comparing the relative costs and carbon intensities of distributed and utility-scale resource acquisition strategies, our approach optimized its distributed system but took the prices and carbon intensities of utility-scale resources as given at their current, empirical values. Optimizing the design and operation of the centralized electricity and water infrastructures was beyond the scope of this paper, as we adopted the perspectives of households and communities. Nevertheless, future work attempting to compare the relative economics and environmental impacts of centralized and distributed electricity and water provision could view both systems as amenable to optimization on their respective scales.

3.6.5 Future directions and implications

Beyond investment insights, investigating how to optimally operate both DETs and DWTs alone or in coordination is an interesting problem without a clear solution. It requires optimizing under uncertainty (Zhang et al., 2020), creating market incentives for all stakeholders including owners, utilities, and grid operators, and possibly creating a new distribution system that can accommodate their small and intermittent nature (Kristov et al., 2016). Furthermore, a new distribution system where supply and demand are aggregated at the community level would make the model less complex, easier to understand, and significantly easier to solve. Adding these insights to the investment insights would go a long way toward encouraging adoption of distributed technologies. Lastly, DETs and DWTs can provide emissions benefits and reduce the investments in large infrastructure upgrades by shrinking utility demand. This was briefly explored in this study but is worth expanding on in future works.

Acknowledgments

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Chapter 4

Climate Risk Management in Agriculture Using Alternative Electricity and Water Resources: A Stochastic Programming Framework

4.1 Introduction

As climate change intensifies and essential resources like water become more scarce, planning for these risks has become essential. To address these needs, we create a two-stage stochastic programming framework that makes first-stage investment decisions for alternative water and electricity capacity additions under climate uncertainty and second-stage operational decisions after the uncertainty is realized. In this work, we apply this framework to an agricultural setting where climate uncertainty and water scarcity present risks not just for farm owners but for everyone. Therefore, the main objectives of this case study are to investigate how a farm can manage the risk of climate uncertainty, how water scarcity affects its operations, and to examine how well this framework performs at advising a decision maker on the investments they can make to mitigate both climate uncertainty and resource scarcity.

Prolonged droughts associated with climate change and increased water withdrawals at unsustainable rates, from sources like aquifers, have placed a significant strain on water resources for both municipal and agricultural uses. In fact, some farmers have found it more profitable to sell water rather than use it to grow crops (Sengupta, 2021). As the population grows, there will be less water from traditional sources available for agriculture. However, there are unconventional sources of water that could become profitable inputs to agricultural production when conventional water or crop prices increase. These unconventional water sources can be far below ground and/or have higher concentrations of contaminants like salt. Finding cost-effective ways to access these unconventional water sources and then applying treatment as necessary to help make agricultural production more robust in the face of climate and weather uncertainties is essential to preserve increasing scarce water resources.

In this paper, we propose a model that maximizes profit by balancing crop yield, water treatment and pumping costs, and the costs of the electricity required to pump and treat the water. Integrated food-energy-water systems allow for the flexibility to take advantage of the cost savings and resources that would not be available if a farm relied only on centralized resources. Under scarce conventional water supplies, a farm faces a decision between reducing production through deficit irrigation and leveraging alternative water resources to continue producing large quantities of crops. Importantly, leveraging alternative water resources typically requires additional energy inputs and this energy could be obtained from the grid or from distributed energy resources. These investments would have to be balanced against an unknown climate and weather where the amount of precipitation available could vary wildly from year-to-year. Therefore, we develop a framework for farm investment decisions structured as a two-stage stochastic quadratically constrained linear program (QCLP) that maximizes farm profit over a 25-year period while considering an uncertain future climate and the costs of investing and operating various electricity and water technologies.

To investigate our main objectives, we compare solutions where the weather and climate are known before an investment decision is made (Perfect Information), the climate but not the weather are known before the investment decisions (Known Climate Unknown Weather), investment decisions are made by hedging all possible climates and weathers (Stochastic), and investment decisions are made based on the average climate (Expected Value).

To investigate different climate futures we create four representative climates — Dry,

Dry-Moderate, Moderate, and Wet — that inform a Markov chain that produces annual precipitation values that correlate with a given climate. For example, the Dry climate is more likely to produce low precipitation years and the Wet climate is more likely to produce high precipitation years.

Furthermore, we consider two different climate probability distributions — Equally Probable and Dry Most Likely — that represent different beliefs that the decision maker might have about the likelihood of each climate scenario occurring. The Equally Probable probability represents the belief all climates are equally likely and the Dry Most Likely probability represents the belief that the Dry climate is the most likely. The decision maker needs these climate probability distributions in order to make an investment decision.

Our model shows that climate uncertainty is the biggest factor affecting potential profit and weighting your investment based on a climate that does not occur can severely impact profits. Optimally hedging investment decisions can balance this downside risk, but when the possible climates trend towards a moderate climate, optimally hedging provides little benefit over simply preparing for the average possible climate. Nonetheless, even though climate uncertainty is the biggest factor affecting profit, the year-to-year weather variability for a given climate can also cause significant swings in profit. The variability in precipitation from year-to-year can erode profits by having an alternative water and/or electricity investment be undersized one year and oversized another. Understanding how these uncertainties can affect a farm's optimal investment decisions and by extension their profit is vastly important, and this model provides a framework to provide these insights.

The remainder of the paper is organized as follows. Section 4.2 reviews relevant literature on climate risk management, food-energy-water modeling, and crop production functions. Section 4.3 details the framework formulation, solution types, model parameterization, and the climate and climate probability distribution calculations. Section 4.4 details the results of the study and Section 4.5 summarizes the most significant findings.

4.2 Background

4.2.1 Climate Risk Management

The main driving force for this work is understanding how climate uncertainty and accompanying resource scarcity will impact agricultural operations and what can be done to mitigate that. This subsection addresses the literature related to climate uncertainty.

As climate change takes hold, extreme weather events and resource scarcity are expected. These uncertainties will affect decision makers who make a wide variety of decisions from energy decisions (Leibowicz, 2018), climate policy (Moreno-Cruz and Keith, 2013), and economics via carbon pricing (Nordhaus, 1992).

In the agricultural setting, climate change has already impacted the livelihood of farmers in the Ecuadorian Andes (Blackmore et al., 2021), the Northern Ethiopian Highlands (Adamseged et al., 2019), and Sub-Saharan Africa (Guido et al., 2020). As a result, how farmers should respond to these climate risks is becoming more important.

Anderson and Kyveryga (2016) illustrated how long-term climate data and observations could be used to quantify climate risks. Wheeler and Lobley (2021) surveyed UK farmers to determine how and/or if they were adapting to increased climate risk and if the creation of farmer specific tools would help farmers adapt to climate risks. We created the framework outlined in this work to be an adaptable tool that farmers could use to access and prepare for climate risk.

In Texas, the uncertainty in water planning presents the biggest problem for the heavily agricultural state. Werner and Svedin (2017) found that the Texas water plan does not adequately prepare for climate change. Furthermore, Jones and van Vliet (2018) note that water scarcity in Texas is not only a result of increasing water withdrawals, but of increasing water salinity. Nonetheless, researchers have increasingly investigated how to adapt to climate risks in Texas, for example Shrum et al. (2018) investigated how a Texas ranch could adapt to water scarcity to maintain protein production. Nielsen-Gammon et al. (2020) provided general insights into how different drought and climate projections could help Texas water planners prepare for a climate uncertain future. The same water uncertainty and potential scarcity that affects the water supply also directly affects crop growth for farmers. This study tests our framework by using a water constrained farm in Texas as a case study.

This work expands upon the climate change management literature by creating a framework that allows farmers to tailor a strategy to mitigate climate risk and resource scarcity. This framework investigates the how different climate futures could affect farmers via the investment decisions they will have to make in the present and how those investment decisions and the climate will affect their operational decisions in the future.

4.2.2 Food-Energy-Water modeling

Our model investigates three distinct sectors — food, energy, and water — that each have their own distinct modeling literature. As drought, climate change, and urbanization stress fresh water sources, alternative water research is becoming especially important.

Alternative water sources like brackish water are popular alternatives to groundwater (LBG-Guyton Associates, 2003). Furthermore, research, like Blinco et al. (2017) which investigated how to optimize the operation and design of systems that use alternative water sources like wastewater treatment and desalination, is another area of interest. However, the work by Arroyo and Shirazi (2012), which detailed the brackish water treatment facilities in Texas and their costs, provides the technological foundation of our work.

Nonetheless, as the operations of food, energy, and water systems become more intertwined, so does the modeling literature. Therefore, for the remainder of this subsection we investigate the literature related to food-energy-water modeling that can help us with our own formulation.

There has been a recent trend in research that has investigated how energy and water systems could be designed together to reduce costs or deal with environmental impacts. Jones and Leibowicz (2021) investigated how the co-optimization of community scale distributed water and energy systems could reduce costs and Vitter et al. (2018) investigated how a community scale wastewater treatment plant could be more cost effective than centralized wastewater treatment. Yet, research related to how food, energy, and water could all be designed together has remained sparse.

Nonetheless, after Heady (1954) developed one of the first uses of linear programming in farming by creating a simple model that maximizes farm profit, modeling farm operations has expanded to not only include the crops, but the technology to get water to the crops and to produce the electricity to power the water systems. Ghasemi (2018) modeled an agricultural microgrid that includes the irrigation water requirements, a water reservoir, an agricultural products packing factory, the lighting load requirements, and other electrical items. Campana et al. (2013) created a dynamic modeling tool of a PV water pumping system that includes a water demand model, a solar PV model, and a pumping system model for quick design and validation. Then Campana et al. (2015) expanded their previous work by modeling how a PV powered pump watering system could be paired with a crop growth model. Zhang et al. (2018) elevated this modeling paradigm further by creating an integrated modeling system that combined a dynamic land ecosystem model, an optimization based economic model, and a regional climate model.

Our model follows this tradition of integrated food-energy-water modeling and expands it by placing an emphasis on optimizing investment decisions under climate uncertainty. However, we take a slight detour from the trends to larger and more integrated systems by limiting our technology choices and keeping the scale to a single farm.

4.2.3 Crop production functions

Crop functions are empirically determined functions that relate water depth, soil salinity, water salinity and more with crop yield. In order to model crop growth, we need a crop function that can be integrated into our modeling framework. Therefore, in this subsection we examine different crop functions and their uses throughout the literature.

There is a large body of work that seeks to mathematically define the relationship between crop yield and soil water depth for a variety of crops.

Barrett and Skogerboe (1980) compiled a list of different types of crop functions calculated over the years looking at linear functions, non-linear functions, how the timing of water affects growth, and the relationship between yield and evapotranspiration. Zhang and Oweis (1999) investigated the water-yield relationship for wheat in the Mediterranean Region and developed easy to interpret linear and quadratic yield functions. Foster and Brozović (2018) researched how to simulate crop yields based on irrigation and rain by investigating the difference between additive crop yield functions and multiplicative crop yield functions while taking into account water timing. Specifically, they created a crop-water growth model that addresses the disadvantages of the crop-water coefficient model when addressing the timing of water deficits. Smilovic et al. (2016) also modeled a crop coefficient model that takes into account how the timing of watering impacts a crop's yield. They use two coefficients, a crop coefficient and a scarcity index, to correct for timing and location. The end result is what they call a crop kite which relates deficit irrigation to yield while taking into account timing.

However, for this work we sought a crop function that took into account over-watering and salt concentration but didn't actively model water timing to save on complexity. So, we use the model developed by Dinar et al. (1991) which estimated a set of yield production functions using water quantity and quality, soil salinity, and drainage volume.

4.3 Methodology

4.3.1 Model formulation

Our framework for farm investment decisions creates a stochastic quadratically constrained linear program (QCLP) to capture the quadratic relationship between crop growth and water inputs. The QCLP maximizes farm profit over a 25-year period. The stochastic QCLP represents a case where a decision maker makes a set of investment decisions before a climate is realized and then makes operation decisions based on that set of investment decisions once the climate is known. We investigate different solution cases, but they all use the same general QCLP formulation, including parameters and variables. The main differences between the solution cases are if the set of investment decisions are fixed or endogenous to the model, if the climate and/or weather is uncertain or not, which climate(s) is (are) being investigated, and what probability is given for each climate to occur in the future. In this section, we outline the model formulation, including parameters, variables, and equations.

Instance Input Parameters:

I	Set of weather realizations
Y	Set of years (1-25)
ha	Size of farm (hectares [ha])
$price$	Price of crop ($ / tonne)
c_{aw}	Unit cost of alternative water ($ / ha-cm)
c_{iw}	Unit cost of irrigation water ($ / ha-cm)
c_{ae}	Investment cost of alternative electricity ($ / kW)
c_{ue}	Unit cost of utility electricity ($ / kWh)
eu_{aw}	Unit energy use of alternative water (kWh / ha-cm)
eu_{iw}	Unit energy use of irrigation water (kWh / ha-cm)
scw	Salt concentration in water (dS / m)
scs	Salt concentration in soil (dS / m)
iwl	Irrigation water limit (hectares-cm)
gsm	Growing season months
cfs	Capacity factor solar
$mhrs$	Hours in a month

$rain_{i,y}$ Precipitation in weather realization i and year y (ha-cm)

QCLP Decision Variables:

$capacity^{AW} \in \mathbb{R}_{\geq 0}$	Invested capacity of alternative water (ha-cm)
$capacity^{AE} \in \mathbb{R}_{\geq 0}$	Invested capacity of alternative electricity (kW)
$water^{Total}_{i,y} \in \mathbb{R}_{\geq 0}$	Total amount of water used (ha-cm) in weather realization i and year y
$water^{IW}_{i,y} \in \mathbb{R}_{\geq 0}$	Total amount of irrigation water used (ha-cm) in weather realization i and year y
$water^{AW}_{i,y} \in \mathbb{R}_{\geq 0}$	Total amount of alternative water used (ha-cm) in weather realization i and year y
$elc^{Total}_{i,y} \in \mathbb{R}_{\geq 0}$	Total amount of electricity used (kWh) in weather realization i and year y
$elc^{AE}_{i,y} \in \mathbb{R}_{\geq 0}$	Total amount of alternative electricity used (kWh) in weather realization i and year
$elc^{UE}_{i,y} \in \mathbb{R}_{\geq 0}$	Total amount of utility electricity used (kWh) in weather realization i and year y
$cy_{i,y} \in \mathbb{R}_{\geq 0}$	Crop yield (tonnes / ha) in weather realization i and year y
$profit_i \in \mathbb{R}_{\geq 0}$	Profit (\$) in weather realization i

4.3.1.1 Objective function

The framework is driven by profit which is equal to the revenue from selling the crop minus the costs of the water and electricity inputs as shown in Equation 4.3.1.1.

$$\text{profit} = \overbrace{\sum_{i\in I}\sum_{y\in Y} ha * price * cy^{i,y}}^{\text{Revenue}} - \overbrace{capacity^{AW} c_{aw} - \sum_{i\in I}\sum_{y\in Y} water^{IW}_{i,y} c_{iw}}^{\text{Water Cost}} - \overbrace{capacity^{AE} c_{ae} - \sum_{i\in I}\sum_{y\in Y} elc^{UE}_{i,y} c_{ue}}^{\text{Electricity Cost}}$$

(4.1)

4.3.1.2 Crop yield function

Crop production functions use the relationship between water depth and salinity to predict crop growth. In these crop production functions, crop yield is a function of water depth, water salinity, soil salinity, and in some cases, other variables. In this model, we calculate crop growth every year for every weather realization. Equation 4.13 in Section 4.3.6 shows the fully parameterized equation.

4.3.1.3 Investment decision equations

Each optimization problem makes a single alternative water investment decision and a single alternative electricity investment decision regardless of the number of weather realizations. This replicates how a decision maker would have to make a single set of investment decisions over a wide range of possibilities. How much capacity the decision maker decides to invest in governs how many alternative resources are available for a given year as shown in Equations 4.2 and 4.3.

$$capacity^{AW} \geq water^{AW}_{i,y}, \forall i \in I, \forall y \in Y \tag{4.2}$$

$$capacity^{AE} * cfs * mhrs * gsm \geq elc^{AE}_{i,y}, \forall i \in I, \forall y \in Y \tag{4.3}$$

4.3.1.4 Operational decision equations

The farm decision maker decides how much groundwater and/or alternative water to provide for his crops to supplement the exogenously specified precipitation and how to supply the power needed for those water sources either through a centralized utility or installed alternative electricity capacity. These decisions are governed by balance equations which ensure that the endogenously specified demands for water and electricity are satisfied. These balance equations are encoded in Equations 4.4, 4.5, and 4.6. Note, precipitation cannot be controlled by the farm and any rain must count toward the crop production function; this is enforced by Equation 4.7. Also, to simulate future resource constraints, irrigation water is limited, as shown in Equation 4.8.

$$rain_{i,y} + water_{i,y}^{AW} + water_{i,y}^{IW} \geq water_{i,y}^{Total} \forall i \in I, \forall y \in Y \tag{4.4}$$

$$elc_{i,y}^{AE} + elc_{i,y}^{UE} \leq elc_{i,y}^{Total} \forall i \in I, \forall y \in Y \tag{4.5}$$

$$water_{i,y}^{AW} eu_{aw} + water_{i,y}^{IW} eu_{iw} \geq elc_{i,y}^{Total} \forall i \in I, \forall y \in Y \tag{4.6}$$

$$water_{i,y}^{AW} eu_{aw} + water_{i,y}^{IW} eu_{iw} \geq elc_{i,y}^{Total} \forall i \in I, \forall y \in Y \tag{4.7}$$

$$water_{i,y}^{IW} \leq iwl, \forall y \in Y \tag{4.8}$$

4.3.2 Model solution types

We analyze the farm's decisions using the three main stochastic programming solutions: Perfect Information, Expected Value, and Stochastic. We also develop a solution where the climate is known like the Perfect Information scenario but the weather is not and call this solution Known Climate Unknown Weather.

4.3.2.1 Stochastic solution formulation

Equation 4.9 shows the general two-stage stochastic program formulation (Leibowicz, 2018) which represents the Stochastic solution in this study.

$$\begin{aligned} \max_{x,(y_\omega)\omega\in\Omega} z^{SS} &= c^T x + \mathbb{E}_\omega d_\omega^T y_\omega \\ s.t. \quad Ax &= b \\ B_\omega x + C_\omega y_\omega &= f_\omega \quad \forall \omega \in \Omega \\ x, y_\omega &\geq 0 \quad \forall \omega \in \Omega \end{aligned} \tag{4.9}$$

In this formulation, the first stage objective function coefficients (the c vector) which in our problem represent the costs of investment and the first stage constraints (the A matrix and the b vector) which in our problem represent the capacity limits of those investments are known with certainty. The second-stage objective function coefficients (the d_ω vector) and the second-stage constraints (the B_ω and C_ω matrices and the f_ω vector) are uncertain when the first-stage decisions (the x vector) are made, but are known when the recourse decisions (the y_ω vector) which in our problem represent the operational decisions are determined. The ω subscripts, which in this study represent a weather vector, symbolize that the parameters and decision variables represent a subset of our representation of the world which in this study is the set of all weather realizations for all climates ($\omega \in \Omega$). The objective is then maximized over all states of our representative world, where the probability of a given state is $p(\omega)$. The single objective function (z^{SS}) produced from the Stochastic solution is the objective value.

The Stochastic solution represents a feasible decision set that optimally hedges for a given set of weather realizations. Optimally hedging for all possible weather realizations will at worse perform the same as the Expected Value solution and should perform better. The difference between the objective value of the Stochastic solution (z^{SS}) and the expected value of the Expected Value solutions (z^{EV}) is called the Value of the Stochastic Solution (VSS). However, the Stochastic solution will at best perform as well as the Perfect Information solution and likely significantly worse. The difference between the expected value of the Perfect Information solutions (z^{PI}) and the Stochastic solution (z^{SS}) is called the Expected Value of Perfect Information (EVPI).

4.3.2.2 Perfect Information solution formulation

The Perfect Information solutions each solve an optimization problem for a single weather realization (ω). Each solution produces a set of investment decisions (x_ω) and a set of operational decisions (y_ω) that are based on that solution's weather realization. This contrasts with the Stochastic solution, where the solution produces one set of investment decisions for all the weather realizations and not a solution for a single weather realization like a Perfect Information solution. After a Perfect Information solution is created for each weather realization, a weighted average of the objective values for each solution (z_ω) are used to produce the expected value of the Perfect Information solutions (z^{PI}). The mathematical formulation of a Perfect Information solution and the expected value of the Perfect Information solutions are shown in Equation 4.10.

$$\begin{aligned} \max_{x_\omega, y_\omega} z_\omega = c^T x_\omega + d_\omega^T y_\omega, \quad \forall \omega \in \Omega \\ \mathrm{z}^{PI} = \mathbb{E}(z_\omega) = \textstyle\sum_{\omega \in \Omega} p(\omega) z_\omega \end{aligned} \tag{4.10}$$

The expected value of the Perfect Information solutions represents the maximum expected profit from a given set of climates and weather realizations. This maximum expected profit is then used as a baseline to compare how the other solutions perform and to determine the EVPI.

4.3.2.3 Expected Value solution formulation

The Expected Value solution makes a single set of investment decisions ($x_{\bar{\omega}}$) based on the average climate ($\bar{\omega}$) rather than by taking into account all the possible combinations of weather and climate like the Stochastic solution. Then, that single set of investment decisions ($x_{\bar{\omega}}$) is used to determine the operational decisions (y_ω) for each weather realization (ω). After an Expected Value solution is created for each weather realization, a weighted average of the objective values for each solution (z_ω) is used to produce the expected value of the Expected Value solutions (z^{EV}). The mathematical formulation of an Expected Value solution, and the expected value of the Expected Value solutions are shown in Equation 4.11.

$$
\begin{aligned}
\max_{x_{\bar{\omega}}, y_{\omega}} z_{\omega} &= c^T x_{\bar{\omega}} + d_{\omega}^T y_{\omega}, \quad \forall \omega \in \Omega \\
z^{EV} &= \mathbb{E}(z_{\omega}) = \sum_{\omega \in \Omega} p(\omega) z_{\omega} \\
s.t. \quad x_{\bar{\omega}} &\in argmin \quad c^T x + d_{\bar{\omega}} y_{\bar{\omega}} \\
\bar{\omega} &= \mathbb{E}(\omega) = \sum_{\omega \in \Omega} p(\omega) \omega
\end{aligned} \tag{4.11}
$$

The Expected Value solution illustrates naïve investment decision making where a decision maker does not take into account all the possible climates and weather realizations and instead only makes a decision based on an average climate. This Expected Value solution can then be compared to a Stochastic solution that makes an investment decision by optimally hedging on the complete set of possible climate and weather outcomes.

4.3.2.4 Known Climate Unknown Weather solution formulation

The Value of Perfect Information, while informative, represents a solution that is impossible to perform as well as, where not only would you know the climate for the next 25 years but the exact weather and rainfall for the next 25 years as well. While the future climate and weather are both uncertain, the climate is more likely to be accurately predicted than the weather making climate more "knowable". We postulate that a metric where the climate for the next 25 years is known but every weather fluctuation is not would provide a better point of comparison for this particular model. Therefore, we created the Known Climate Unknown Weather solution where even if we perfectly understand climate change, there will still be weather variability across years that cannot be perfectly predicted.

A Known Climate Unknown Weather solution makes a single set of investment decisions ($x_{\omega'}$) and operational decisions (y_{ω}) based on the set of weather realizations ($\omega \in \omega'$) in a given climate (ω'). After a Known Climate Unknown Weather solution is created for each climate, a weighted average of the objective values for each solution ($z_{\omega'}$) is used to produce the expected value of the Known Weather Unknown Climate solutions (z^{KCUW}). The mathematical formulation of a Known Climate Unknown Weather solution, and the expected value of the Known Climate Unknown Weather solutions are shown in Equation 4.12.

$$\begin{gathered}
\max_{x_{\omega\prime},(y_\omega)\omega\in\omega\prime} z_{\omega\prime} = c^T x_{\omega\prime} + \mathbb{E}_\omega d_\omega^T y_\omega \quad \forall\omega' \in \Omega \\
s.t. \quad Ax_{\omega\prime} = b \\
B_\omega x_{\omega'} + C_\omega y_\omega = f_\omega \quad \forall\omega \in \omega' \\
x_{\omega'}, y_\omega \geq 0 \quad \forall\omega \in \omega' \\
z^{KCUW} = \mathbb{E}(z_{\omega'}) = \sum_{\omega\in\omega'} p(\omega')z_{\omega'}
\end{gathered} \tag{4.12}$$

Like the Stochastic solution, the Known Climate Unknown Weather solution represents a feasible decision set that optimally hedges for a given set of weather realizations; however, the Known Climate Unknown Weather hedges based on the weather realizations of a single known climate. Therefore, the Known Climate Unknown Weather solution will at worse perform the same as the Stochastic solution and at best perform as well as the Perfect Information solution. We call the difference between the objective value of the Stochastic solution (z^{SS}) and the expected value of the Known Climate Unknown Weather solutions (z^{KCUW}) the Expected Value of Known Climate (EVKC) and the difference between the expected value of the Perfect Information solutions (z^{PI}) and the expected value of the Known Climate Unknown Weather solutions (z^{KCUW}) the Expected Value of Known Weather (EVKW).

4.3.3 Climate Probability Distributions

The climate probability distributions are designed to help us address our primary research questions and hypotheses. Specifically, we are interested in understanding how the probabilities of a range of climates affect investment decisions in alternative energy and water, how those investment decisions perform in different climate realizations, both predicted and not, and how the variation of weather realizations in a given climate affects profit.

The climate probability distribution is also used to create the appropriate number of weather realizations. For example, the Equally Probable climate probability has 1000 weather realizations from each climate totaling 4000 samples. The Dry Most Likely has 2400 weather realizations from the Dry Climate, 1000 from the Dry-Moderate climate, 400 from the Moderate climate, and only 200 weather realizations from the Wet climate for a total of 4000 samples. The climate probability distributions and their abbreviations are listed below.

- Equally Probable (EP) - where all four climates are equally likely to occur.
- Dry Most Likely (DML) - where the Dry climate is most likely to occur (60% chance) and where the Dry-Moderate, Moderate, and Wet climates have a 25%, 10%, and 5% chance of occurrence respectively. These climate probabilities reflect researchers' expectations that the future climate of Texas will be drier than it is at present (Nielsen-Gammon et al., 2020)

4.3.4 Climates and the weather generation Markov chain

We define four distinct climates that produce yearly weather realizations presented as annual precipitation values. The four climates are Dry, Dry-Moderate, Moderate, and Wet. The Wet climate has the highest probability for a high precipitation year followed by the Moderate, Dry-Moderate, and Dry climates in that order.

Each climate is defined by a Markov chain that generates a weather realization and by extension an annual precipitation value for each year. Table 4.1 shows the probability of an annual precipitation value for a given climate, which corresponds to the Markov chain's stationary distribution.

Furthermore, each Markov chain generator can be run multiple times to represent numerous possible weather samples. Because of the stochastic nature of these Markov chains, samples for a given climate can have significantly different weather realizations. To ensure that the objective values for the solutions and any subsets provide tight confidence intervals, we run 4000 samples for each solution and each subset represents between 200 - 2400 samples. Table 4.2 illustrates the distribution statistics of the climates for the Equally Probable solutions where each climate Markov chain is sampled 1000 times.

Table 4.1. Probability of a given value of annual precipitation in inches by climate

Climate	5 inches	15 inches	30 inches	45 inches	60 inches
Dry	20%	50%	25%	5%	0%
Dry-Moderate	5%	25%	55%	10%	5%
Moderate	20%	20%	20%	20%	20%
Wet	0%	5%	20%	45%	30%

Table 4.2. Annual precipitation distribution statistics by climate

Climate	1st Quartile	Median	Mean	3rd Quartile
Dry	15 inches	15 inches	18.3 inches	30 inches
Dry-Moderate	15 inches	30 inches	27.93 inches	30 inches
Moderate	15 inches	30 inches	30.96 inches	45 inches
Wet	45 inches	45 inches	45.09 inches	60 inches

4.3.5 Technologies

To keep the model limited in size, the decision maker can only choose between two technologies for electricity and two technologies for water. The alternative water technology is a reverse osmosis system which takes brackish water with a total dissolved solid (TDS) concentration up to 3.5 g/L — which would include the majority of Texas brackish water resources (LBG-Guyton Associates, 2003). The decision maker can also choose to irrigate via a groundwater source which requires electricity for the pumps as outlined in Table 4.3; however, the amount of groundwater available for use is limited to simulate water scarcity.

The alternative electricity technology is photovoltaic solar (solar PV), where the decision maker decides what size solar farm to invest in. The costs, as shown in Table 4.3, include installation, inverters, and other ancillary equipment needed for a solar farm installation. And if the decision maker does not wish to invest in alternative electricity, the decision maker can simply choose to purchase electricity from the utility for a conservatively low price of $ 0.08 / kWh.

We assume that the pumping system to retrieve and distribute water, brackish or fresh, already exists and that the irrigation system has negligible water losses. Effective precipitation can be significantly lower than actual precipitation and is a function of the evapotranspiration rate of the crop, the amount of precipitation and many other factors including the genetic makeup of the crop (Masoner et al., 2000; Dastane, 1978; Sharma et al., 2019). To simplify the model, we define the exogenously defined precipitation as effective precipitation or the amount of precipitation that is utilized by the crop for growth.

4.3.6 Performance and cost data

Table 4.3 reports the performance and cost assumptions for each technology and parameter in the model, including operational energy use. Equation 4.13 shows the quadratic crop production for wheat from Dinar et al. (1991) to model crop growth in this model.

Table 4.3. Main performance and cost assumptions for technologies and a documentation of data sources.

Technology / Parameter	Capital Costs	O&M Costs	Energy Use	Other	Source
Utility Electricity	-	$ 0.08 / kWh	-		[36]
Solar	$ 1500 / kW	-	0.30 capacity factor		[66]
Groundwater	-	$7 / acre -in	1 kWh / kGal		[4; 133]
Desalination	$ 0.40 / kGal		6.5 kWh / m^3		[108; 7; 71]
Farm Size				200 hectares	[159]
Price of Wheat				$ 200 / tonne	[164]
Salt Concentration Water				1.0 dS / m	[45]
Salt Conentration Soil				2.0 dS / m	[45]
Irrigation Water Limit				0.5 acre-ft / acre /yr	[163]

$$\begin{aligned} cy^{i,y} \leq -3.350 + 0.2064 * water^{Total}_{i,y} - 0.0014 * water^{Total}_{i,y} * water^{Total}_{i,y} + \\ -0.071 * water^{Total}_{i,y} * scw + 0.033 * water^{Total}_{i,y} * scs + 3.555 * scw + \\ 2.326 * scw^2 - 2.031 * scs + 0.823 * scs^2 - 2.754 * scw * scc, \quad \forall i \in I, \forall y \in Y \end{aligned} \tag{4.13}$$

4.4 Results

In this section, we present, compare, and discuss results from our scenarios. We begin by examining the differences between the Stochastic (Stoch) solution and the expected objective values for the Perfect Information (PI), Expected Value (EV), and Known Climate Unknown Weather (KCUW) solutions. These comparisons allow us to calculate the Expected Value of Perfect Information (EVPI), the Value of the Stochastic Solution (VSS), the Expected Value of Known Weather (EVKW), and the Expected Value of Known Climate (EWKC). Then we dive deeper by comparing all the Known Climate Unknown Weather solutions to the investment decisions (which remain the same) and the operational decisions of the Stochastic solution for each climate. In this deeper dive we compare how the profit, crop yields, investment decisions, and operations of both water and electricity differ by climate for the Known Climate Unknown Weather and Stochastic solutions.

4.4.1 Expected objective values and summary statistics

Figure 4.1 shows the expected objective values for all solutions and Table 4.4 shows the EVPI, VSS, EVKW, and EVKC. As expected, both climate probability distributions follow the general pattern $z^{PI} \geq z^{KCUW} \geq z^{Stochastic} \geq z^{EV}$ and there is significant value in having perfect information.

However, the value of knowing the climate drives most of the EVPI while knowing the weather adds only a small amount of value. Furthermore, the Expected Value solutions provide virtually the same amount of value as the Stochastic solution despite the sophistication of the Stochastic solution. Although, because of the limited value in knowing the weather compared to the climate, optimally hedging for the weather is expected to provide limited value.

Table 4.5 shows summary statistics for all solutions. While the standard deviations are relatively large for both profit and crop yield, the 95% confidence intervals for all scenarios, even the ones with only 200 samples, are extremely tight, implying that the expected profits approach the true means.

Table 4.4. The Expected Value of Perfect Information (EVPI), Value of the Stochastic Solution (VSS), Expected Value of Known Weather (EVKW), and Expected Value of Known Climate (EVKC) by climate probability distribution

Climate Probability	**EVPI**	**VSS**	**EVKC**	**EVKC**
Equally Probable	\$108,725.10	\$0.49	\$10,396.32	\$98,328.78
Dry Most Likely	\$76,606.01	\$940.90	\$11,740.03	\$64,865.98

4.4.2 Profit comparisons: Stochastic vs. Known Climate Unknown Weather solutions

After showing the expected objective values in the subsection above, in this subsection we compare the profits of all the Known Climate Unknown Weather solutions and calculate

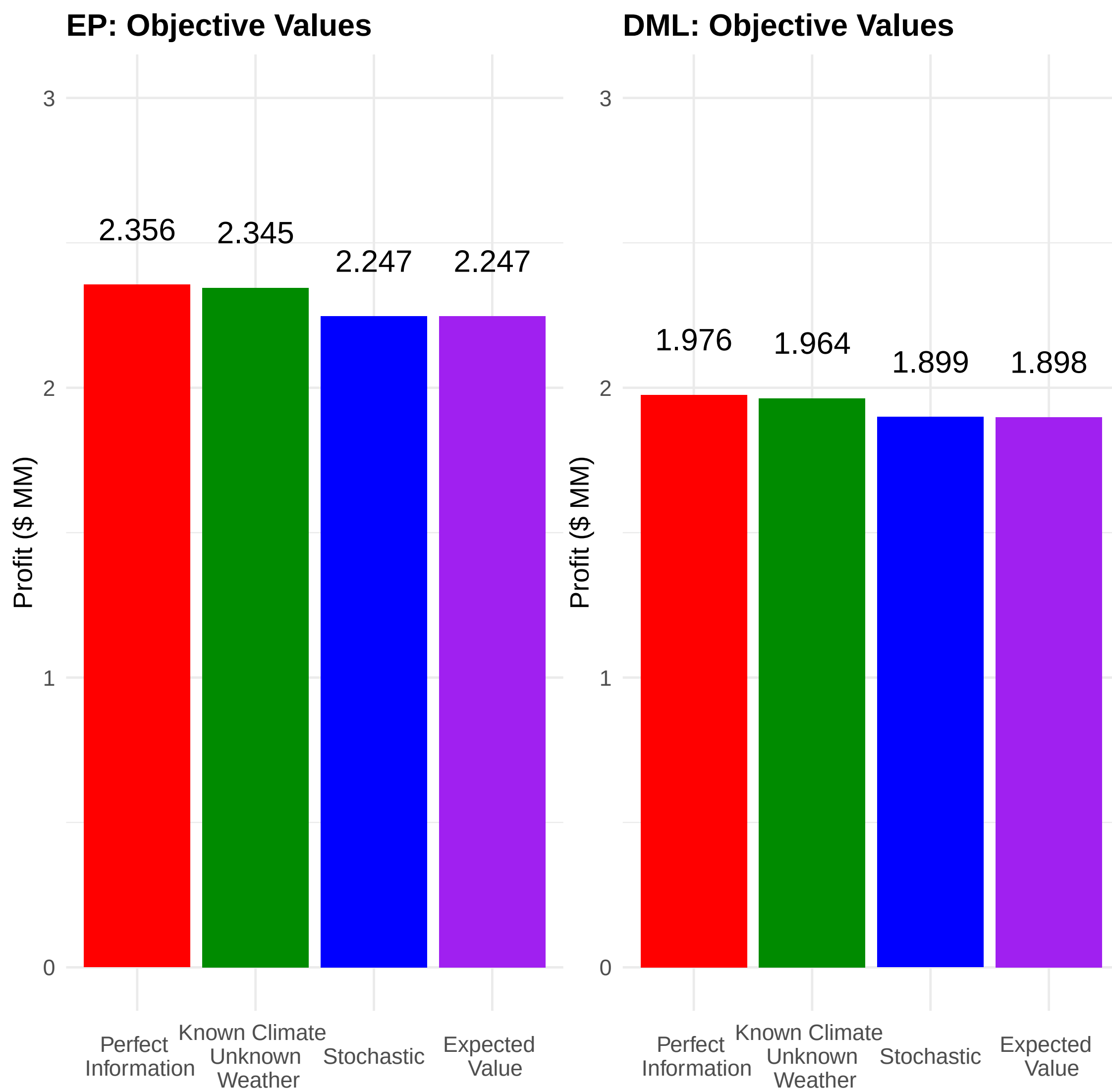

Figure 4.1. The expected profits by climate probability distribution and solution

the profits for each climate in the Stochastic solution by first calculating the profit for each weather realization in a given climate by adding the cost of the operation decisions of a weather realization to the fixed investment decisions costs and then averaging the

Table 4.5. Summary statistics for the profit and crop yield (CY) of all the solutions (Perfect Information [PI], Stochastic [Stoch], Expected Value [EV], Known Climate Unknown Weather [KCUW]) by Climate Probability (Equally Probable [EP] and Dry Most Likely [DML])

Solution	Profit Mean	Profit Std Dev	Profit 95% CI +/-	CY Yearly Means	CY Std. Dev.	CY 95% CI +/-
EP-PI	2,355,663	635,133	19,691	2.866	0.909	0.00564
EP-KCUW	2,345,267	640,497	19,857	2.835	0.964	0.00598
EP-Stoch	2,246,938	616,454	19,112	2.674	1.114	0.00690
EP-EV	2,246,937	616,518	19,114	2.674	1.114	0.00690
DML-PI	1,975,827	490,655	15,212	2.771	0.840	0.00521
DML-KCUW	1,964,087	489,987	15,191	2.757	0.866	0.00537
DML-Stoch	1,899,221	424,374	13,157	2.666	0.929	0.00576
DML-EV	1,898,280	408,033	12,650	2.713	0.895	0.00555

profit of every weather realization in a given climate. We show not just the differences but investigate the reasons for these differences in profit which include average yearly precipitation differences and yearly weather variability.

4.4.2.1 Drivers of profit variability

Figure 4.2 — which shows the average profit via the bars and bar labels on the left y-axis — illustrates that as expected the Wet Climate Known Climate Unknown Weather scenarios produce the highest profits for both climate probability distributions (note in this section we are only comparing the Known Climate Unknown Weather and Stochastic solutions, the Known Climate Unknown Weather solutions still underperform the Perfect Information solutions). And in general, the average yearly precipitation — tracked for each scenario by a black square with its values corresponding to the right y-axis — was a reliable predictor of profit for most climates. Also as expected, the Dry climates were the least profitable; however, the Moderate climates have a lower average total profit than the Dry-Moderate climates.

These results add to the findings from the preceding subsection, where it was shown that there is value in knowing the weather for both climate probability distributions, that not just precipitation but the variability in precipitation matters when making investment decisions. Even if a certain climate has a higher maximum precipitation value which in turn raises the yearly average precipitation value, a tighter range and/or a higher median which reduces variability can reduce investment cost. More variability could lead to more investment that is underutilized in wetter years or insufficient capacity — that needs to be supplemented or in some cases that simply does not provide the optimal amount of water — in leaner years. This will be explored in the following subsections.

4.4.2.2 Profit comparisons

Figure 4.2 shows that the profits in the Stochastic solution for each climate, which all make the same investment decisions for a given climate probability distribution, all have profits less than or equal to their corresponding Known Climate Unknown Weather solution, which make different investment decisions depending on the climates.

Figure 4.2 shows that there can be a significant difference between the Stochastic solution for a given climate and its corresponding Known Climate Unknown Weather solution. Nonetheless, if the Stochastic solution's investment decisions are close to its corresponding Known Climate Unknown Weather solution's decisions, the profit gap will be minimal. However, if the investment decisions are significantly different, this can lead to significantly lower profits. In the Dry Most Likely scenarios, that are shown in Figure 4.2, the investor heavily weighs the probability of a Dry Climate. So, the difference between the Known Climate Unknown Weather and Stochastic Dry Climate solutions are minimal, but the differences between the Known Climate Unknown Weather and Stochastic profits for all other climates are significant. In other words, if the climate does not end up being Dry, the investment decisions made would be poorly aligned with any other climate realizations and come with significant costs. This will be explored in the following subsections.

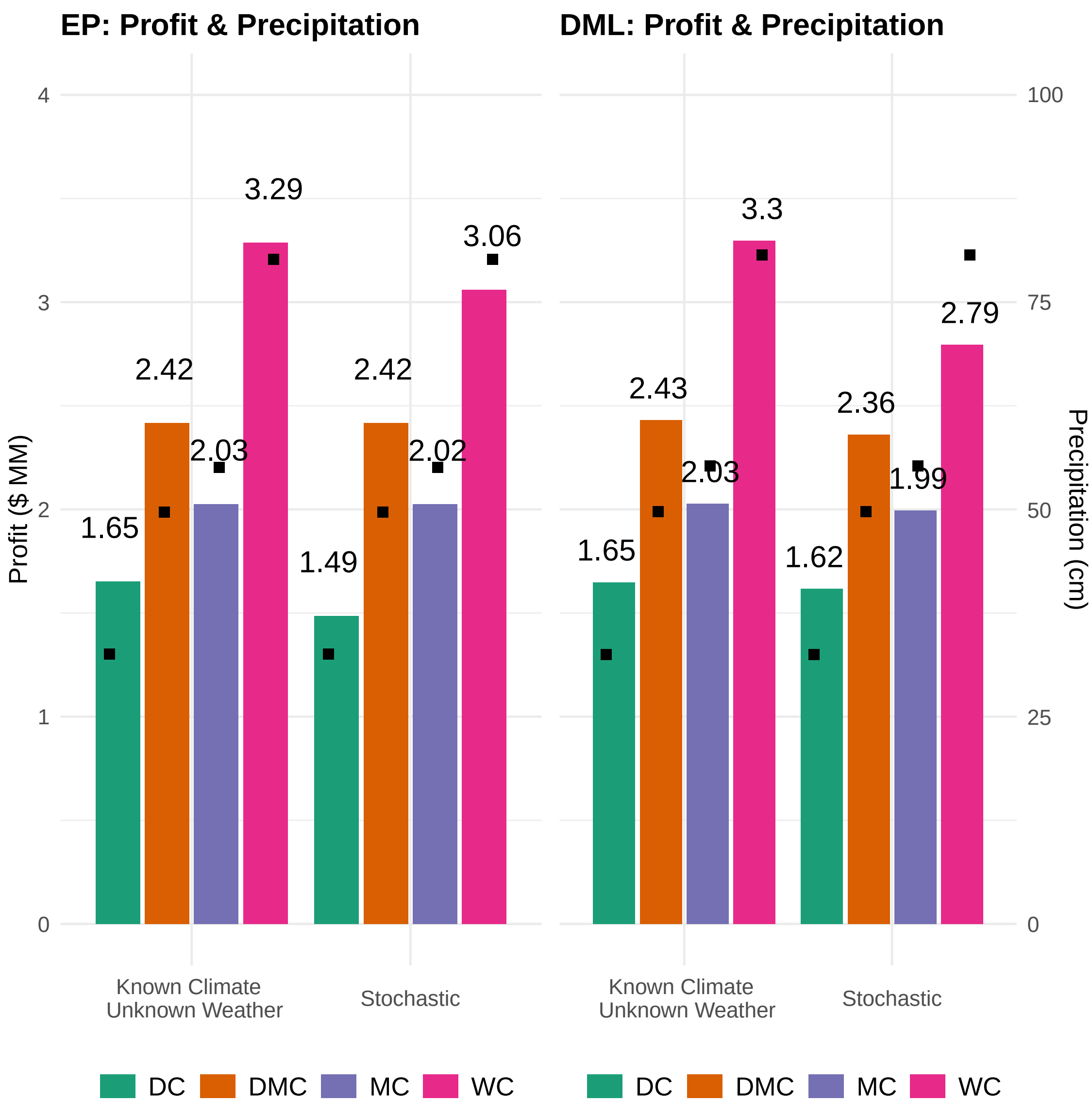

Figure 4.2. Average total profit and average yearly precipitation: Stochastic vs. Known Climate Unknown Weather solutions by climate probability distribution

4.4.3 Wheat yield comparisons: Stochastic vs. Known Climate Unknown Weather solutions

Figure 4.3 shows that average annual wheat yields — illustrated with the bars and bar labels that correspond with the left y axis — do correlate with average total profit more so than average yearly precipitation. In this figure, we tracked average annual water depth, using the black triangles, instead of precipitation on the right y axis. This shows that increased average annual water depth does not necessarily lead to a proportional increase in crop yield. In the Known Climate Unknown Weather solutions the average yearly water depth for the Dry, Dry-Moderate, and Moderate climates are roughly the same but their wheat yields differ significantly.

These results suggest that there are a variety of factors that affect wheat yield. The most obvious factor is that the wheat yield function is a quadratic production function where overwatering actually decreases yield. Furthermore, like for profit, the variability in weather and precipitation values can cause some years to have a high yield while others have a significantly lower yield. And finally, the Dry solutions are able to better tailor their optimal water use because most years the amount of water they receive via precipitation is below their optimal water level and they can use alternative water technologies to reach but not exceed those optimal water levels. These factors will be explored in the following subsections.

4.4.4 Reverse osmosis capacity and solar PV investment decisions: Stochastic vs. Known Climate Unknown Weather solutions

In this subsection, we investigate how reverse osmosis capacity and solar PV capacity investment decisions differ across solutions. We look into why a given solution invests in a specific amount of reverse osmosis capacity and/or solar PV capacity and investigate potential causes for the variations including average yearly precipitation values and yearly

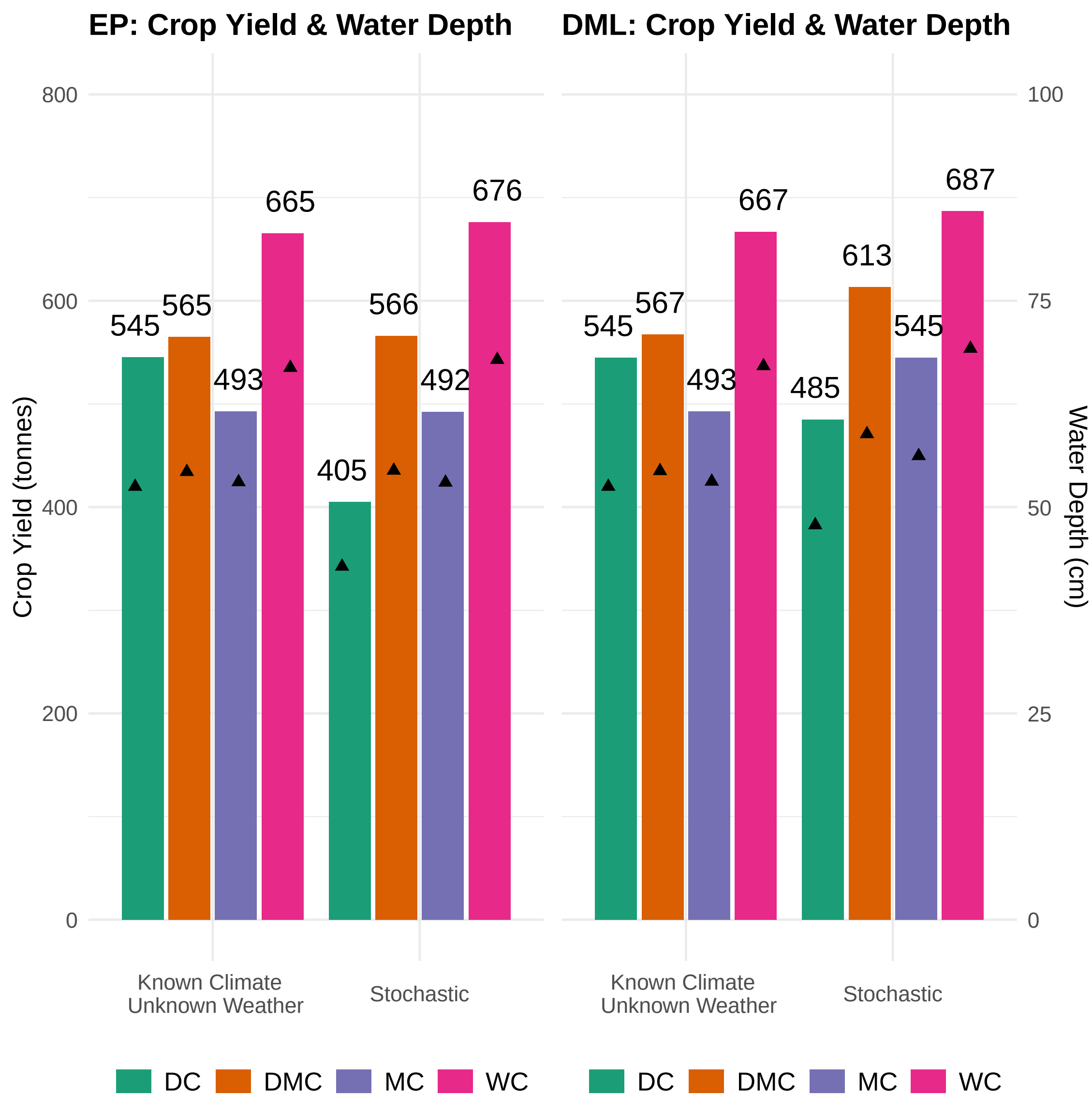

Figure 4.3. Average annual wheat yields and water depth: Stochastic vs. Known Climate Unknown Weather solutions by climate probability distribution

weather variability.

Figures 4.4 and 4.5 show that the Dry climate Known Climate Unknown Weather solutions invest the most in reverse osmosis capacity and solar PV capacity to make up for their shortcomings in precipitation. On the other hand, the Wet climate Known Climate Unknown Weather solutions do not invest at all in either because of their surplus of precipitation. Nonetheless, the moderate climates do not show a correlation between more precipitation and more investment.

This further highlights how weather variability among climates — more so than the average precipitation — drives investment decisions and can create inefficiencies in investments that drive up costs. The Moderate climate solutions invest in more reverse osmosis capacity than the Dry-Moderate climate scenarios because the model wants to ensure access to water in the dryer years. However, it invests in less solar PV capacity than the Dry-Moderate climate solutions because most years it does not need as much reverse osmosis capacity and by extension solar PV capacity due to higher rainfall in certain years and in the dryer years it can use utility electricity to meet any additional electricity demand. These conflicting investment decisions drive year-to-year inefficiencies that affect profit.

While the Known Climate Unknown Weather solutions are able to make different investment decisions based on the climate, the Stochastic and Expected Value solutions are only able to make a single set of investment decisions for all possible climate and weather realizations. Furthermore, the Stochastic solution makes an optimal decision by optimally hedging against all possible weather outcomes (which is simulated by 4000 possible weather outcomes), but the Expected Value scenario only optimizes its decision based on a single expected value weather realization. For the Dry Most Likely Expected Value solution this leads to a slightly different decision than the corresponding Stochastic solution which results in a small Value of the Stochastic Solution as shown in Table 4.4, but for the Equally Probable climate probability distribution the Expected Value and Stochastic solution investment decisions and by extension expected profits are virtually identical.

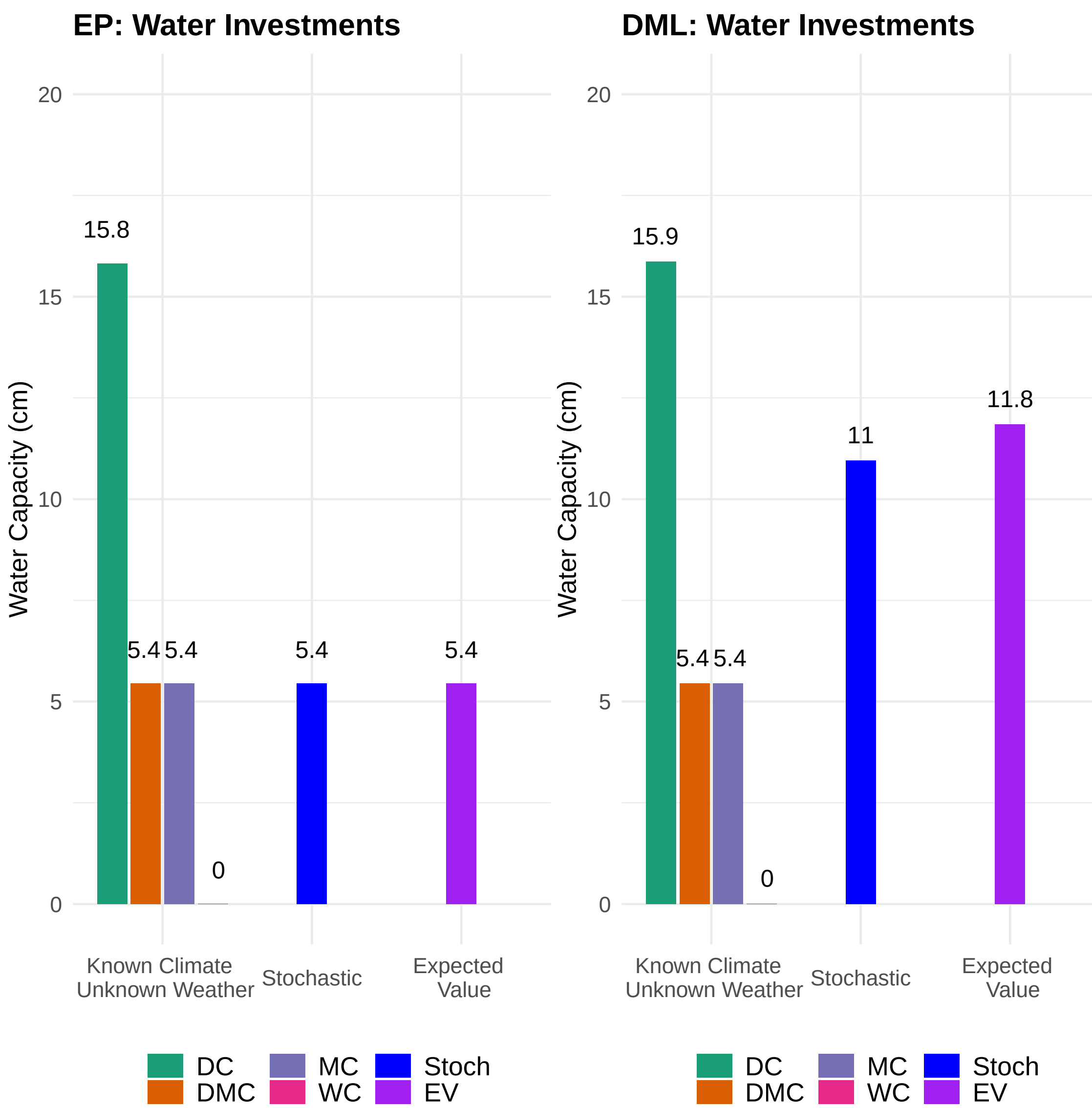

Figure 4.4. Reverse osmosis capacity investment decisions: Stochastic vs. Known Climate Unknown Weather solutions by climate probability distribution

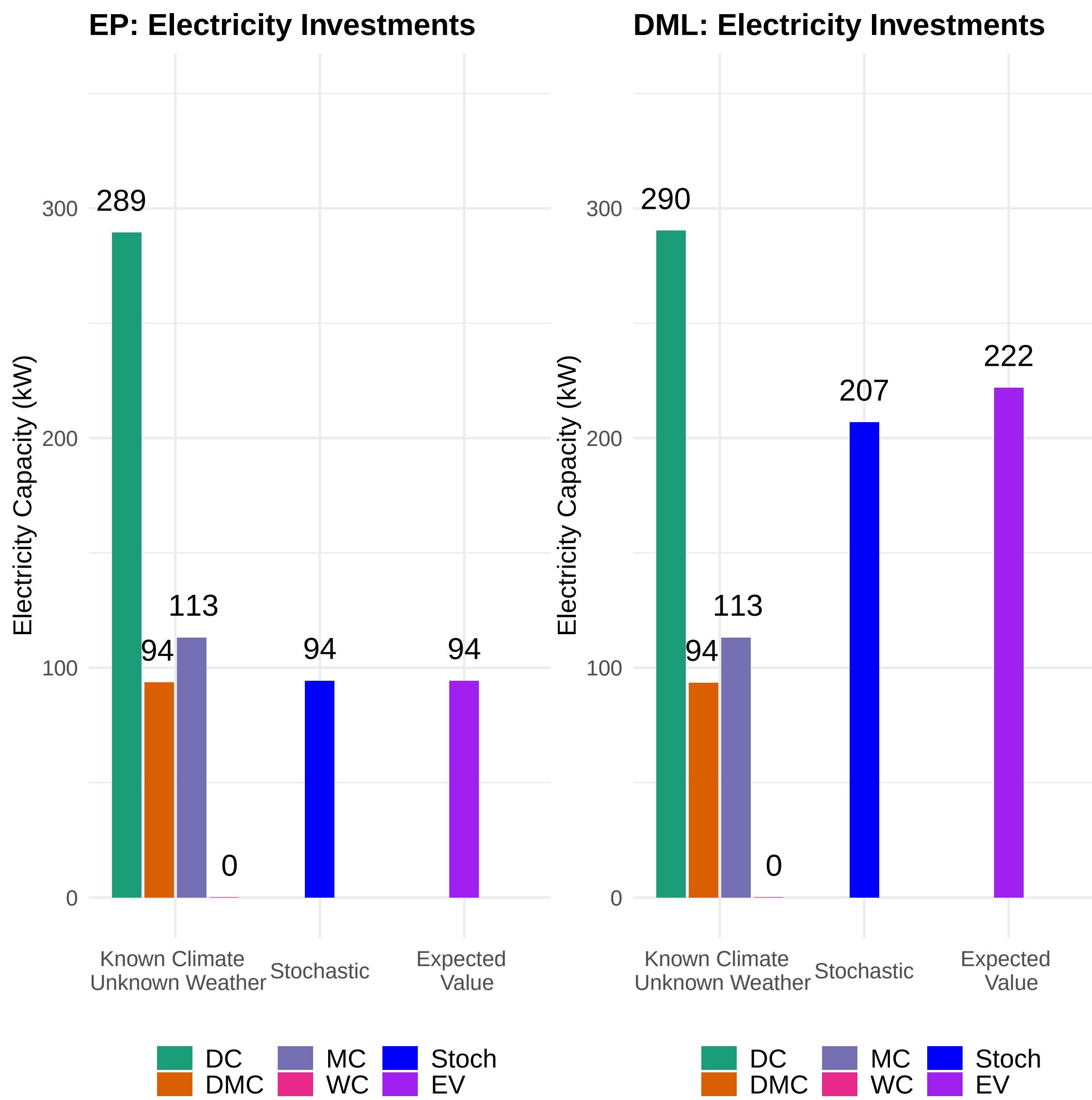

Figure 4.5. Solar PV capacity investment decisions: Stochastic vs. Known Climate Unknown Weather solutions by climate probability distribution

4.4.5 Water operations: Stochastic vs. Known Climate Unknown Weather solutions

In this subsection, we investigate how the reverse osmosis capacity investment decisions affect water operations across scenarios. We look into why a given scenario invests in a specific amount of reverse osmosis capacity, how that affects operations, and investigate potential causes for the variations, including relationships between alternative water and groundwater use.

Figure 4.6 shows that the relatively moderate investment in reverse osmosis capacity by the Equally Probable Stochastic solutions results in less water capacity than is optimal for the Dry climate solutions, even with increased groundwater use. This results in less water being available for the crops and a subsequent reduction in crop yield and profit compared to the Known Climate Unknown Weather solution as shown in Figures 4.2 and 4.3. However, for the Dry-Moderate and Moderate climates the investment and as a result the operations are nearly identical.

On the other hand, Figure 4.6 shows the large investments in reverse osmosis capacity by the Dry Most Likely Stochastic solution results in more reverse osmosis capacity than is optimal for all the climates save the Dry climate. This results in an oversupply of relatively expensive reverse osmosis capacity. The increasing usage of reverse osmosis water even though it leads to an increase in crop yield as shown in Figure 4.3 leads to a decrease in profit because of the extra expense as shown in Figure 4.2.

4.4.6 Electricity operations

In this subsection, we investigate how the solar PV capacity investment decisions affect electricity operations across scenarios. We look into why a given scenario invests in a specific amount of solar PV capacity, how that affects operations, and investigate potential causes for the variations including variations in water use.

In general, solar PV capacity investments match reverse osmosis capacity investments and solar PV electricity use matches reverse osmosis water use. However, there are solutions where the investments in solar PV do not align with the optimal amounts of solar PV electricity. Figure 4.7 clearly illustrates that the solar PV electricity used in the Dry climate

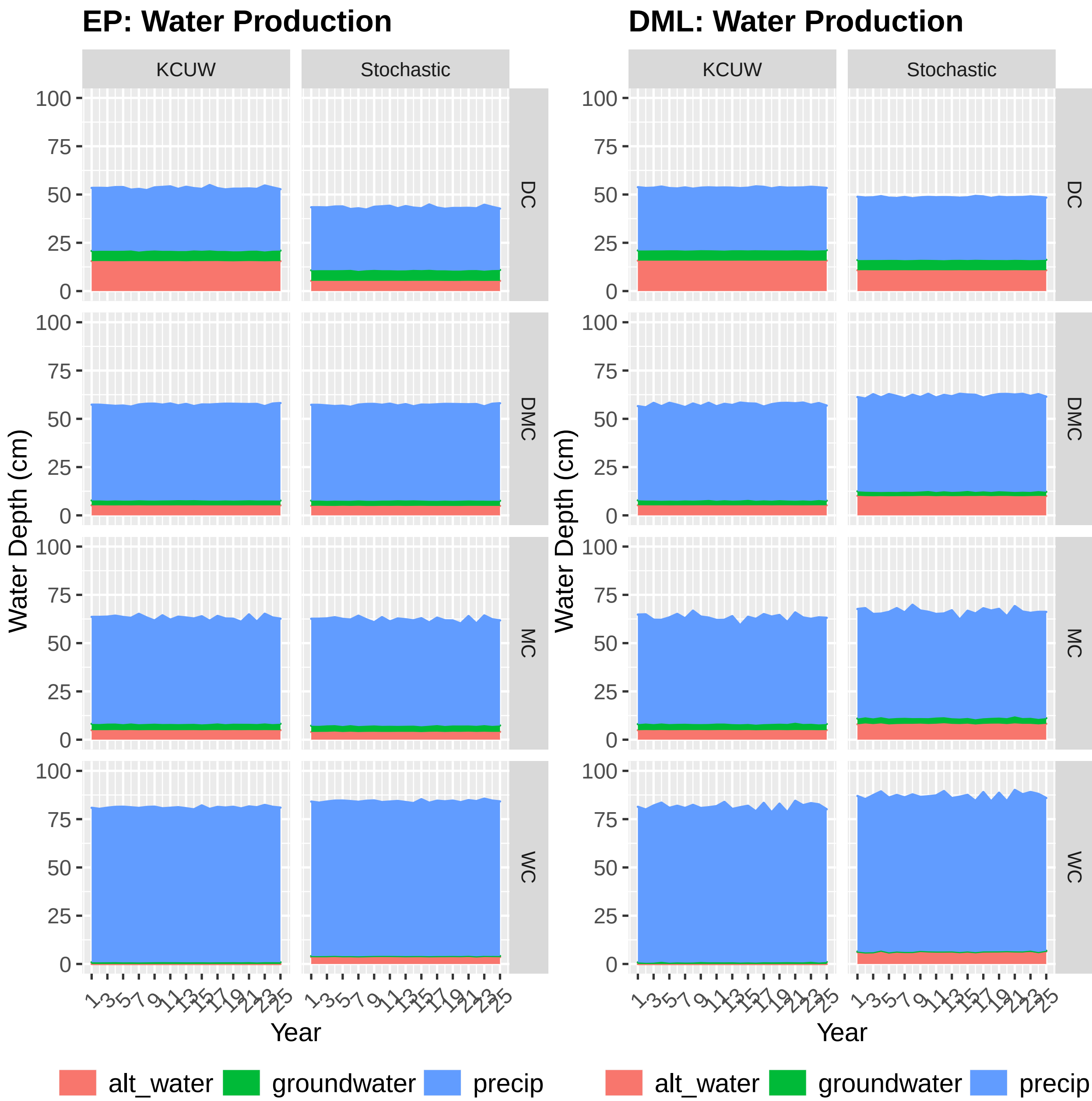

Figure 4.6. Annual water operations: : Stochastic vs. Known Climate Unknown Weather solutions by climate probability distribution

Equally Probable Stochastic solution is much less than in the corresponding Known Climate Unknown Weather solution. However, rather than increase its utility electricity use to fill in any gaps, it simply uses less water than what is optimal. The decrease in water used — because of the groundwater limits and the reduced investment in reverse osmosis capacity — is the most significant factor in the reduction of electricity use. This implies that reverse osmosis water use is the main driver for electricity use.

This is further emphasized in Figure 4.7 where excess electricity does not lead to higher water usage in the Dry Most Likely solutions. While the investments in solar PV capacity do crowd out utility electricity, they do not encourage greater use of reverse osmosis water. This further supports the implication that reverse osmosis water use drives solar PV capacity investment.

4.4.7 Summary statistics: Stochastic vs. Known Climate Unknown Weather solutions

The profit and wheat crop yields reported in Figures 4.2 and 4.3 are average values and as such represent a range of values. In order for these mean values to have significance, we calculated the 95% confidence intervals to ensure that our calculated mean values were indeed close to the true mean. The confidence intervals for profit and crop yield for all scenarios are extremely tight (less than +/- $0.03 MM for profit and less than +/- 0.027 tonnes for crop yield) and show that the calculated means are very close to the true mean.

The standard deviations, on the other hand, encompass a much wider range of values and depend on the climate and climate probability distribution. A climate with a skew to certain weather realizations, like the Wet and Dry climates, has a smaller standard deviation than the Moderate climate where all weather realizations are equally likely. This reinforces the reasoning that variation in weather realizations heavily influences profit even more than average precipitation.

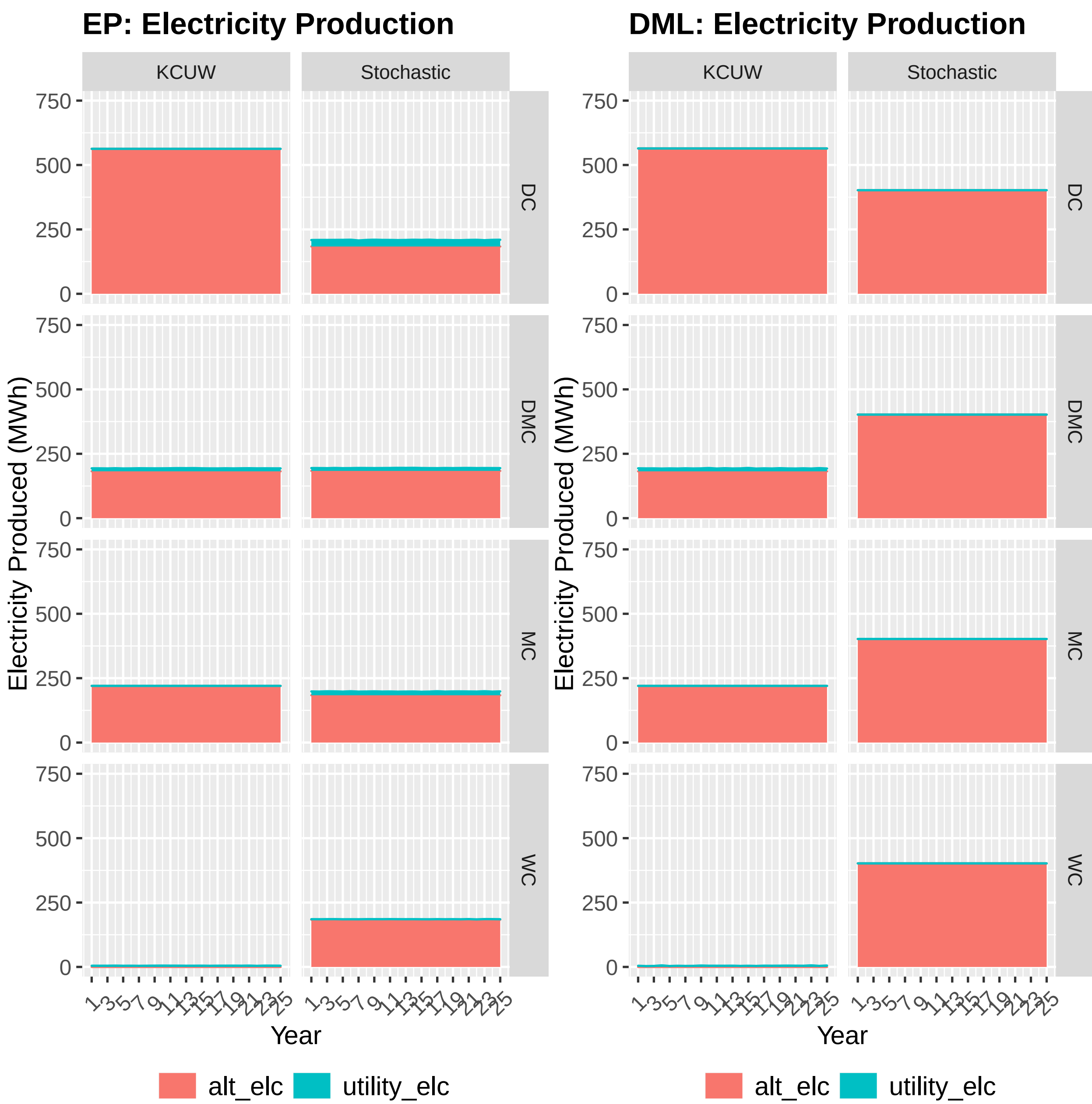

Figure 4.7. Annual electricity operations: : Stochastic vs. Known Climate Unknown Weather solutions by climate probability distribution

Note, while the Equally Probable solutions' climates all had 1000 samples, the Dry Most Likely scenarios' climates' samples ranged from 200 samples to 2400 samples, which affects both the standard deviation and confidence intervals. However, this does not result in major differences and all the general trends mentioned above still hold. All the means, standard deviations, and 95% confidence interval statistics are shown in Tables 4.6 and 4.7.

Table 4.6. Equally Probable climate probability distribution: summary statistics for the profit and crop yield (CY) of the Stochastic (Stoch) and Known Climate Unknown Weather (KCUW) solutions by climate (Dry [DC], Dry-Moderate [DMC], Moderate [MC], Wet [WC])

EP Scenario	Profit Mean	Profit Std Dev	Profit 95% CI +/-	CY Yearly Means	CY Std. Dev.	CY 95% CI +/-
DC-KCUW	1,652,488	170,907	10,611	2.726	0.762	0.00944
DC-Stoch	1,486,498	253,577	15,744	2.024	1.146	0.01421
DMC-KCUW	2,416,584	206,384	12,813	2.824	0.865	0.01072
DMC-Stoch	2,416,521	206,139	12,798	2.830	0.867	0.01075
MC-KCUW	2,025,712	291,547	18,101	2.464	1.344	0.01667
MC-Stoch	2,024,500	297,946	18,498	2.462	1.343	0.01665
WC-KCUW	3,286,282	106,040	6,584	3.327	0.439	0.00544
WC-Stoch	3,060,232	79,790	4,954	3.381	0.318	0.00394

Table 4.7. Dry Most Likely climate probability distribution: summary statistics for the profit and crop yield (CY) of the Stochastic (Stoch) and Known Climate Unknown Weather (KCUW) solutions by climate (Dry [DC], Dry-Moderate [DMC], Moderate [MC], Wet [WC])

DML Scenario	Profit Mean	Profit Std Dev	Profit 95% CI +/-	CY Yearly Means	CY Std. Dev.	CY 95% CI +/-
DC-KCUW	1,648,352	170,789	6,838	2.724	0.765	0.00612
DC-Stoch	1,616,243	206,780	8,279	2.425	0.941	0.00753
DMC-KCUW	2,430,358	196,029	12,171	2.836	0.847	0.01050
DMC-Stoch	2,361,189	153,639	9,539	3.066	0.664	0.00824
MC-KCUW	2,026,811	301,300	29,654	2.464	1.354	0.02654
MC-Stoch	1,994,689	244,732	24,086	2.725	1.074	0.02106
WC-KCUW	3,296,111	110,519	15,449	3.335	0.427	0.01184
WC-Stoch	2,794,189	59,309	8,291	3.434	0.209	0.00581

4.5 Conclusions

In this model, there are two main uncertainties that the farm decision maker must consider: the future climate and the year-to-year precipitation amounts within that climate. These uncertainties affect a decision maker's investment decisions which in turn affect the operations of the farm, followed by the crop yield and finally the profit.

The climate uncertainty is the biggest factor affecting profit as illustrated by the relatively large difference between the Stochastic and Known Climate Unknown Weather solutions, but the much smaller difference between the expected value of the Known Climate Unknown Weather and Perfect Information solutions. More conservative investment decisions can balance this downside risk and even increase the upside if more moderate climates are realized, as shown in the Equally Probable solutions. However, if the climate will actually be at one of the extremes, then more aggressively hedging more towards that climate will provide a higher profit than a more conservative investment as shown by the Dry Most Likely solutions.

Nonetheless, optimally hedging seems to provide limited benefit compared to simply preparing for the average possible climate. The Stochastic solution's investment decisions and the Expected Value solution's investment decisions are nearly identical for the Equally Probable climate probability distribution. For the Dry Most Likely climate probability distribution, there is only a slight difference between the Stochastic and Expected Value solutions' investment decisions. Nonetheless, this reflects that the defined climate probability distributions are relatively moderate where the average climate and by extension precipitation values are close to the given Moderate and Dry-Moderate climates. Climate probability distributions where the average never occurs, like a 50% chance of a Wet Climate and a 50% chance of a Dry Climate, would likely increase the Value of the Stochastic Solution.

While climate uncertainty is the biggest factor affecting profit, the year-to-year weather variability for a given climate can also cause significant swings in crop yield and therefore profit. In fact, the differences in profit between the Perfect Information solutions, where the climate and the weather are known, and the Known Climate Unknown Weather solutions, where the climate is known but the weather is uncertain, are larger than the Values of the Stochastic solutions.

The swings in precipitation from year-to-year can corrode overall profits by having a reverse osmosis capacity and/or solar PV capacity investment be undersized one year and oversized another. The extra costs incurred because of the mismatch between invested capacity and the year-to-year optimal capacities — even when the invested capacity matches the yearly average optimal capacity — add up. This explains why the Moderate climate scenarios are less profitable than the Dry-Moderate climate scenarios, even though the Moderate climate has a higher average yearly precipitation value.

While both of these uncertainties are outside of the farmer's control, especially with regards to the weather variations for a given climate, understanding how a decision maker's investments and by extension their profits could be affected by these uncertainties is important. For instance, a more risk-taking operator might be more willing to heavily weigh a specific climate to maximize upside than a more risk-averse operator. This model allows an operator to examine how climate probability distributions affect profit for a variety of climate realizations not just based on what he believes the climate will be, but on a representative sample of climate possibilities in order to provide the operator with a fuller picture on how investment decisions in the present could affect profits in the future.

4.5.1 Limitations

This model provides a general framework for farm investment and operational decisions, but does not answer detailed questions about water schedules or even solar production. It abstracts many of the day-to-day operational decisions in exchange for a big picture year-by-year framework which could significantly affect profit and yield. Other works in this area of research have done the opposite and have added more detailed information and have added more sectors like energy, climate, and water treatment to the basic crop yield model to provide even more accurate insights. We believe our simpler model allows for more insights on a larger variety of scenarios; however, we concede it sacrifices accuracy. Future works could add more day to day or sector specific detail to allow for more accurate insights while balancing the ability for our framework to investigate a large number of scenarios quickly.

4.5.2 Future directions

This model, in the most general sense, is a stochastic framework to help a decision maker deal with climate risk and resource uncertainty. In this study, we investigated how climate uncertainty and water scarcity would affect a farm decision maker's investment and operational decisions to deal with those problems. However, any sector that has to deal with climate uncertainty and resource constraints could benefit from this framework. In the future, this modeling framework could be used to investigate: heating and cooling demand and the generation resources need to meet it, urban food and water demand, energy generation investment decisions, and optimal electricity distribution networks.

Acknowledgments

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Chapter 5

Conclusion

5.1 Summary of findings

These works investigate the potential of flexible demands in a variety of sectors — water, transportation, and agriculture — to lower energy costs, improve energy resilience, and increase the integration of intermittent renewables. Furthermore, they explore how integrating these flexible loads at various scales from the household to the city level can impact costs and adoption. These works use a variety of optimization techniques to investigate scenarios to gather insights into uncertain futures. This adds to the literature by creating a multi-system optimization framework that can be used integrate the design and operation of energy supply and demand systems to achieve mutually reinforcing benefits.

The first main chapter investigated how the electrification of transportation, the flexibility of electric shared autonomous vehicles, and the evolution of the power sector could influence each other, reducing costs and improving energy and carbon intensities. We created scenarios that explored the possible shared autonomous vehicle futures and evaluated those scenarios with a linear optimization framework that explored a time period of 35 years. We found that even if SAVs double vehicle miles traveled they are still cheaper than business as usual. They save money compared to the business as usual case because the SAVs electrify faster than the POVs and are more likely to align their EV charging with the generation of renewables. The ability to align electricity use of any system with production reduces the amount of renewable and battery capacity needed, saving significant amounts of money. We found this trend in the other works and if applied to real systems can help speed up the adoption of cleaner and more efficient technologies even when they have relatively high upfront costs.

The second main chapter focused on the difference in costs between individual and community level decisions and the co-benefits of investing in distributed energy and water technologies. We created scenarios based on both level of aggregation and the ability to invest in distributed energy technologies, distributed water technologies, both sets, or neither and evaluated those scenarios with an annualized mixed integer optimization framework. We found that distributed energy and water technologies are competitive in today's price environment and that they become more competitive when co-optimized and when the number of people investing in them (the aggregation level) increases. Distributed energy and water technologies are able to achieve these cost savings in this environment partly due to the tiered rate structure of the current energy and water utilities. Distributed energy and water technologies, by reducing the amount of electricity and water purchased from the utilities at the higher and more expensive tiers, save significant amounts of money especially when they are aggregated with large groups of investors and/or co-optimized. Co-optimization also significantly lowers carbon intensity by having virtually carbon free distributed energy technologies provide the electricity for relatively energy intensive distributed water technologies. Co-optimization of any two or more systems has the potential to provide cost and operational benefits and aggregation has the potential to allow for economies of scale and reduce payback periods. These implications could allow for more efficient infrastructure investments and more equitable access. We further explore the concept of co-optimization in our third work.

The third main chapter develops an agricultural case study where a farm has to make alternative water and energy investment decisions for an uncertain climate. We created a stochastic quadratic optimization framework that allows a decision maker to see how applying different weights to the probability of different climates occurring affects investment and operational decisions and by extension profit. The framework compares perfect information scenarios where the climate is certain to the scenarios where the investment decisions are based on the assignment of probabilities. We find that aggressively weighting an extreme climate can help maximize profit if that climate actually occurs, but if the the extreme climate does not occur this decision can severely reduce profit. Nonetheless, even optimal hedging decisions — which generally reduce the profit losses associated with climate uncertainty — can result in volatile profits from year to year due to annual weather variability within each future climate scenario. However, for most climates and probability assignments investing in alternative water and energy technologies can help temper the negative effects of climate uncertainty.

5.2 Contributions and limitations

The works in this dissertation explore how intermittent renewables encourage more flexible loads which in turn help with the integration of intermittent renewables. However, beyond that they explore how this alignment can create other co-benefits that improve the operation of two or more distinct systems. For example in our first work, the electrification of vehicles accelerated by SAVs, if optimally charged, increased the utilization of renewables which reduced the need for expensive battery investments and saved significant amounts of money. Increasing the levels of aggregation, as shown in our second work, encourages the adoption of more distributed technologies which can reduce the strain on centralized infrastructure while providing resilience for residential households. And our third work shows that as a farm decides to invest in more alternative water to combat the uncertainties of future climates, alternative electricity investments increase to meet the extra electricity demand.

These examples highlight only a small fraction of the potential co-benefits of aligning the energy sector with other systems. However, they do imply that there are other benefits that were not explored. For example, the alternative electricity that a farm invests in to power its alternative water resources could be used for other farm operations. Or it could encourage the electrification of farm vehicles like tractors. One of the limitations of these works is their limited scale.

All of these works looked at a relatively small sample space and optimized their decisions while assuming anything outside of that sample space stayed the same. While we believe this to be reasonable it ignores larger scale interactions that could have a significant effect on the results of our work. Furthermore, the two works that looked over a long time horizon were formulated in a way that does not take into account discrete decisions and assumes that all decisions can be represented on a continuous curve. While we believe this simplification still allows us to develop good insights, it can obscure the effects of economies of scale and lead to possibly infeasible investment decisions. The work that we did model these discrete decisions, because we felt at the modeled scale it was necessary to account for the discrete decisions, evaluated only one representative year. This limitation did not allow us to investigate how changes over time could affect the investment or operation decisions. Nonetheless, even with these trade-offs all of our works were able to provide insights that can help decisions makers across a variety of scales and time horizons.

Lastly, the first two works are deterministic and the last work stochasticity is limited to the long-run climate scenarios. The systems we modeled, especially energy and transportation systems, operate under considerable real-time uncertainty. These hour-by-hour and day-by-day uncertainties impact decisions makers everyday and are largely absent from our modeling. Nevertheless, scenario analysis does provide a framework for quick analysis that can be used to make good decisions even in the absence of a formal probabilistic model.

5.3 Future directions

The works in this dissertation can be expanded by either addressing some of the limitations in the modeling framework or by expanding the systems investigated. The limitations of the modeling framework can be corrected by either expanding the models or by changing the model paradigm all together. The models can be expanded by instead of only exploring two or three systems at a time, adding other systems to the model to see how other interactions can either expand the benefits or create extra costs.

All of the included works use scenario analysis to provide insights. However, in some situations decision makers want the model to produce a single decision or possibly a limited selection of decisions that account for any uncertainties. Our third work which uses a two stage stochastic framework does provide a decision under uncertainty, but even then that decision is used as reference point to compare how that decision affects profit compared to the perfect information and realized scenarios. Adopting our frameworks to provide a decision under uncertainty, that decisions makers can directly use could be an important future direction. Optimization schemes that include risk-averse objectives, like those based on Value at Risk (VaR) or Conditional Value at Risk (CVaR), provide a possible framework for this potential direction.

Furthermore, decision makers face different scales of uncertainty — big decisions like large investment decisions which are made a few times and smaller more frequent (e.g. hourly) operational decisions. Future research will need to work to address a way to bridge these scales both in time (sporadic vs. frequent decisions) and space (large scale investments vs. systems level operations).

All of these models use a combination of real world data and projections to inform their parameters and assumptions. Nonetheless, some of this data is out of date, uses data sources that conflict with other data sources, and/or offers limited data verification. Running these models with different data and assumptions could yield different insights. Then all the insights could be compared against a real world system for validation to determine if the framework yields reasonable results.

The models in this dissertation are relatively limited in scale and the number of investigated systems. While the limits allow for more detailed investigation into a specific sector or region, they by definition provide limited insights. Other integrated assessment models look at how multiple sectors interact all at once. These models are able to investigate a vast web of interactions and help decision makers investigate typically opaque interactions. Our framework could be expanded to include other sectors like the industrial sector or simply combine sectors modeled in separate works like transportation and residential buildings.

While some of these larger integrated assessment models are optimization models, as these models increase in size, some shift modeling paradigm. Therefore, expanding the number of investigated systems might require shifting from an optimization model to a different type of model like a simulation or equilibrium model. In fact, simply switching modeling type could yield different insights even without expanding the model. A possible future direction could be to see if the general insights hold under a different modeling paradigm or if they are artifacts of the optimization scheme.

The works in this dissertation provide a general framework for decision makers investigating what energy supply and end-use technologies to invest in, how different sectors interact, and how to reduce the cost of adoption for new renewable and distributed technologies. The works focused on a specific region or case study but can be used for different applications with only simple modifications of the general framework. We hope that future works are able to use this framework for a variety of applications whether by simply changing the database information, by expanding the model, or even by changing the paradigm. Nonetheless, these works expanded the literature on integrated energy modeling and how flexible demands from other sectors can increase the efficiency of energy systems and stimulate renewable utilization and adoption. We hope that this framework is used to drive the adoption of distributed technologies by households of all incomes to help them reduce cost and improve access to the infrastructure needed for modern life.

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